An investigation into the profitability and sustainability of market timing strategies in Real Estate Investment Trusts (REITs): A global perspective

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By

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Abstract

The buying and selling activity of market participants creates dynamic movements in the prices of listed securities. Investors typically aim to realise short term profit from this volatility using market timing strategies. Several studies have explored the reliability of market timing rules across asset classes. The unique properties of Real Estate Investment Trusts (REITs) and the consequent potential predictability in the returns of this asset class has raised the question of whether market timing strategies can be successfully applied to this asset class. This study investigates the effectiveness of market timing strategies on REITs and whether the effectiveness of these strategies persists through market crises. The study covers the period from January 2001 to December 2020 and employs data from six of the largest REITs markets globally – the United States, Japan, United Kingdom, Australia, Brazil, and South Africa. Four market timing strategies are studied: the moving average, time series momentum, modified moving average crossover, and dual momentum, and, as such, the analysis provides a comparison of market timing strategies that are seldom observed together. The effectiveness of these strategies is also tested over three periods covering the Global Financial Crisis, European Sovereign Debt crisis; and the Covid-19 pandemic. In general, the MA and TSM market timing rules exhibited very similar performance while the MMAC and DM market timing rules exhibited the highest returns. Of the four market timing rules, the DM market timing rule exhibited the highest return with the lowest overall risk, indicating that it has the highest predictive ability of the four rules. The findings of this study are useful for investors aiming to generate returns from short-term market fluctuations.

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Chapter 1: Introduction

1.1 Background

Investors often use a buy-and-hold strategy in an attempt to realise long term returns commensurate with the level of risk of the investment. While this strategy may prove effective in the long term, it ignores the possibility of realising greater returns through trading off short-term volatility.

Proponents of the Efficient Market Hypothesis ("EMH") argue that macro and micro information is already embedded into asset prices. Fama (1970), who put forward the EMH, based this assumption on the premise that all investors reach the same consensus about market information. He reasoned that opportunities to generate superior returns are unobserved, and that investors cannot rely on fundamental or technical analysis to achieve superior returns. The EMH describes the notion of "available information" through three forms of the hypothesis. The first form is defined as the weak form and maintains that stock prices have already incorporated information deduced from market data. As a result, investors would have already exploited price signals to forecast stock price movements (Fama, 1970). The second form of the EMH is defined as semi-strong. This form asserts that both technical analysis and fundamental analysis are futile because stock prices would already reflect all publicly available information. The third form of the EMH, the strong form, maintains that stock prices reflect all available public and inside information, and thus investors would not be able to outperform the market in a consistent manner (Fama, 1970). In all its forms, the EMH purports that market participants are rational and therefore markets are efficient. Since the EMH assumes that markets are efficient, the only way to achieve higher returns would be to assume higher levels of risk. Taking this view into account, a buy-and-hold strategy would be most appropriate.

It is difficult to substantiate an efficient market from a practical point of view, since the buying and selling activity of all investors create dynamic movements in the prices of listed securities. Sharpe (1975) and Merton (1981) both allude to the possibility of an investor realising potential short-term profit from forecasting the above-mentioned market dynamic. Sharpe (1975) terms the forecasting mechanism "market timing'', which he defines as rotating between asset classes, depending on whether the market is bullish or bearish. Johannes et al. (2002) also confirm that market timing is an attempt to outperform a buy-and-hold approach by way of forecasting the direction of the market and rotating between asset classes accordingly. The study conducted by Merton (1981) further substantiates the case for deriving profit from market timing. Merton (1981) asserts that profit derived from market timing may be divided into two components. The first component comprises the movement in prices of stocks selected in the stock selection process. The second component comprises the movement in the entire stock market due to stock prices deviating from the security market line (SML)[1], using a market timer. Market timing strategies thus provide investors with the advantage to shift between asset classes in an attempt to realise excess returns from those classes that perform well in bull markets, or consequently those that perform well in bear markets. This allows investors to turn volatility into an advantage and use an alternative method to reviewing their stock selection strategies or opting for a buy-and-hold strategy. Consequently, an investor would require both a precise predictive measure and select the correct asset class in order to generate returns that are superior to that of a buy-and-hold strategy. However, provided markets are at least weak form efficient, attempts to predict future share prices and generate abnormal returns using technical analysis are thus futile, because historical information is already incorporated into the share prices.

Predictive ability further becomes crucial when factoring in the above-mentioned economic cycles. This rationale proposes that the returns for some asset classes are more predictable than others. Empirical research conducted by De Chassart and Dumont (2002) confirms that markets experience bull and bear phases. The authors further investigate the predictive power of market timing strategies under both conditions.

[1] The SML depicts the various levels of systematic risk-expected return relationships for individual stocks, at any given time. Since the line depicts combinations of expected returns with corresponding risk, efficiently priced stocks are placed on the line. Deviations from the SML may include either a point plotted above this line, or a point plotted below this line. A point plotted above the line indicates that the stock is undervalued, since the expected return is greater than the fair return provided for the same corresponding level of systematic risk. A point plotted below the line is indicative of the stock being overvalued, since the expected return is less than the fair return provided for same corresponding level of systematic risk (Bodie, Kane, & Marcus, 2014).

1.1 Problem statement

The model for Real Estate Investment Trusts (REITs) was established in the United States (US) in 1960 and has since become the pioneering framework for establishing REITs in various global locations (Brounen & de Koning, 2012). According to the National Association of Real Estate Investment Trusts (NAREIT) (2019), nearly 40 countries have adopted this framework to establish REITs in their respective locations. Figure 1 depicts the locations where REITs markets exist. The largest REITs markets are those of the US, Japan, United Kingdom (UK), Australia, Brazil, and South Africa (SA)[2]. Evidently, REITs exist in both developed and emerging markets. Quasi-REITs behave more like asset-backed securities rather than conventional equity REITs found in other REITs markets. In order to achieve comparable results in this study, China quasi-REITs have been excluded.

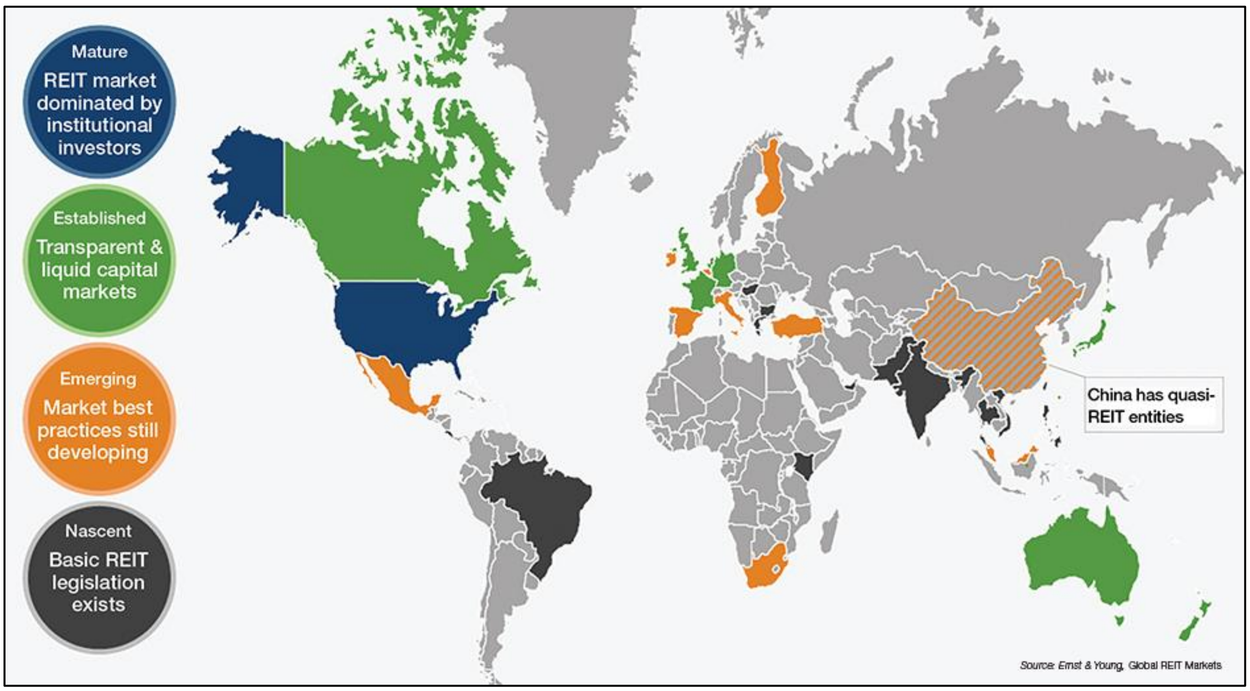

Figure 1:Global REIT markets (Source: Institutional Real Estate Inc, 2020)

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[2] This is according to their market capitalisation and weight (%) in the FTSE EPRA Global REIT Index. The FTSE European Public Real Estate Association ("EPRA") NAREIT Global Real Estate Index Series is designed to represent general trends in eligible real estate equities worldwide. Relevant activities are defined as the ownership, trading and development of income-producing real estate. The index series now covers global, developed and emerging indices, as well the UK's AIM market (NAREIT, 2020).

REITs that are listed in the US own real estate assets that are valued at approximately 2 trillion US dollars, with a market capitalisation exceeding 1 trillion US dollars. This is the largest REITs market globally, accounting for 48.32% of the EPRA NAREIT Global Index[3]. REITs listed in Japan ("J-REITs") represent the largest REITs market in Asia, and the second largest REIT market, internationally (Akinsomi, 2020). The real estate sector in Japan is less focused on property development and more focused on property investing (Newell & Peng, 2012). UK REITs were introduced on the London Stock Exchange in 2007. The sector is composed of more than 50 REITs that own and manage multiple real estate types (London Stock Exchange Group, 2021). UK REITs have a total market capitalisation exceeding 50 billion pounds, qualifying this as the third largest REIT market internationally (Akinsomi, 2020). The Australian Stock Exchange ("ASX") introduced a separate sector for REITs on its main board in 2008. Prior to 2008, Australian REITs ("A-REITs") operated as Listed Property Trusts (LPTs). The mandate of A-REITs extends beyond the reliance on rental income as a primary source of income, which was the sole mandate of LPTs (Australian Investors Association, 2020). A-REITs represent the fourth largest REITs market, internationally (Akinsomi 2020). REITs were introduced in Brazil in 1993, but gained wide traction post the 2008 financial crisis. The increased popularity of this asset class in Brazil is attributable to the legislative changes that allowed Brazilian REITs to expand the scope of real estate types in their portfolios (Yokoyama, Neto, & da Cunha, 2016). According to Akinsomi (2020), this is the fifth largest REITs market globally. Similar to the ASX, the Johannesburg Stock Exchange ("JSE") also created a separate sector on its main board for REITs in 2013, because of the significant demand for this asset class. However, many SA REITs are small in size and subject to less frequent trading, thereby inhibiting efficient pricing

REITs offer investors an alternative entry point into the real estate market, by acquiring shares in companies that own and manage real estate property. Investors are thus able to enter this market without a significant initial outlay of capital generally associated with investing in real estate (Makatsane, 2018). Real estate as an asset class generally offers stable returns with relatively low downside risk, in comparison to other asset classes such as equities. However, it is highly illiquid. The liquid nature of REIT securities, in contrast, provides investors with the flexibility and ease to buy and sell shares without incurring large transaction costs generally associated with buying and

[3] EPRA NAREIT Global Index and author (April 2020).

selling real estate. Another benefit exhibited by REITs is the diversification of risk. Companies in this sector own an array of properties ranging from residential apartments to office blocks. This provides protection of risks arising from investments made only in a specific segment of real estate (Carstens, 2018).

REITs exhibit properties akin to both fixed income and equity securities. The similarity to fixed income securities is represented by the recurring cash flow provided to REIT investors, which acts as the yield earned from income producing properties owned by the REITs. Domestic investors also benefit from the tax advantage provided by the fixed income stream provided by this asset class (Carstens, 2018). A comparative report of global REITs compiled by PWC (2019) finds that dividend income is taxed according to the appropriate tax rate for the shareholder. In tax jurisdictions where REITs exist, domestic investors are either exempt from dividends withholding tax, or are allowed to offset their withholding tax against the income tax payable. Foreign REIT investors are exempt of dividend withholding taxes in all jurisdictions where REIT markets exist. The similarity of REITs to equity is seen by the potential capital appreciation of the underlying assets.

The underlying assets managed by REITs produce consistent cash flows in the form of rental income. The yield earned by REIT investors represents a significant portion of the total return earned by REITs. In turn, REITs qualify for tax exemptions which are calculated according to the rules of the jurisdiction in which the REITs incur taxes, provided that a predetermined portion of their income is distributed (Akinsomi, 2020). According to the South African REIT Association, 75% of the taxable distributable income generated by REITs must be paid to investors. Although REITs located in Australia are required to distribute 90% of their income, 100% of their net income needs to be distributed in order to obtain tax exemption. US REITs and J-REITs are also required to distribute a minimum of 90% of their taxable income to obtain tax exemption, which is the same requirement for UK REITs (PWC, 2019). Brazilian REITs are required to distribute 95% of their income biannually (PWC, 2019). Block (2011) asserts that the distribution requirement reinforces the stability of cash inflows, especially during economic downturns.[4]

[4] During the COVID-19 pandemic, many REITs made arrangements with local finance authorities to maintain their REIT status while still fulfilling the distribution requirement (Akinsomi, 2020). For example, NAREITs opted for US

Nelling and Gyourko (1998) use this consistency in income as a basis for arguing predictability in forecasting the returns of REIT securities. Bradfield et al. (2015) prove that the volatility of REITs and physical real estate are generally lower than the volatility exhibited by non-REIT equity. Liu and Mei (1992) also confirm the stance taken by Bradfield et al. (2015), with the exception of the predictability in the returns of REITs compared to government bonds. They assert that the volatility of REITs, represented by standard deviation, is greater than the volatility exhibited by government bonds. Using data from 1993 to 2014, Aguilar, Boudry and Connolly (2018) investigate the factors that influence the efficiency of REIT prices specifically. The authors find that REITs markets have experience short term inefficiency and long-term efficiency.

According to de Klerk (The South African Institute of Tax Professionals, 2019), REITs are not correlated to asset classes such as bonds, stocks, and cash. In another study, Lee and Stevenson (2005) observe that REITs, represented by the NAREIT index, exhibit extremely low correlation to equities, and even lower correlation to fixed income securities. This provides a strong level of protection for portfolios containing multiple asset classes. A study conducted by Charles, Darné and Kim (2015) examine the price efficiency of gold and silver markets. The authors highlight that in periods of negative market and geopolitical outlooks, investors tend to shift their investments from risky assets to the aforementioned precious metals. This is because the inclusion of precious metals provides a hedge to the investor's portfolio, consistent with the findings of Hillier, Draper and Faff (2006). The preference for precious metals in periods of negative market outlook, together with their low correlation with the returns of non-precious metal stocks exhibits properties that are largely comparable to REITs' securities. Through statistical analysis, the authors find that the efficiency of both precious metal markets have an inverse relationship with predictability in returns. Charles, Darné and Kim (2015) conclude that the gold market exhibits the greatest pricing efficiency and therefore returns least easily predicted in this market.

Investments in real estate are often viewed as a buy-and-hold strategy. However, the unique properties of REITS and the consequent potential predictability in the returns of this asset class has raised the question of whether market timing strategies can be successfully applied to this asset class as well. Market timing strategies have been successfully applied to established REITs

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REITs to meet the distribution requirement through a combination of stock and cash dividends instead of cash dividends only. The SA REIT association opted for a deferral of the dividends payable by SA REITs, until 2022.

markets and continue to be applied in emerging REITs markets. Glabadanidis (2014) finds that the market timing Moving Average (MA) strategy produces consistent profitability for investors investing in individual REITs and REIT indices in the US market over the buy-and-hold strategy. Liu et al. (2019) conclude that market timing may also be successful in the Hong Kong REITs market, since this market exhibits strong persistence and price inefficiency. According to the authors, price trends in these REITs tend to continue in the same direction from one period to the next.

The sole focus on REITs in this study may be further motivated by an investigation into the performance of market timing strategies in the renewable energy sector by Papadopoulos (2017). As with REIT securities, Papadopoulos (2017) observes that the renewable energy sector is still within its growth phase and will continue to exhibit greater trading opportunities as stocks in this sector increase their market share. The market timing strategies employed by the author accounts for stocks of companies that have single and multiple subsectors of renewable energy. This is relevant to this study as REITs typically own and manage real estate that have single and multiple use purposes. The scope for empirical research in REIT securities is wide and, if correctly investigated, may translate into practical application for investors at large to earn excess returns.

Under normal market conditions, the properties exhibited by REITs' securities allow investors to potentially apply market timing strategies successfully. However, these securities are prone to large upside and downside volatility in times of market crises. Newell and Peng (2009) find that A-REITs lost their diversification benefits during the Global Financial Crisis of 2008 (GFC), as these REITs assumed greater debt levels to supplement the loss of tenants. In contrast to Newell and Peng (2009), Simon and Ng (2009) conclude that while US-REIT securities do not lose their hedging ability during market crises, some subsectors of REITs are more volatile than others. Evidently, the behaviour of REITs during market crises are mixed as REITs adapt to their country-specific market conditions to maintain adequate liquidity.

1.2 Research question

This study aims to investigate the effectiveness of market timing strategies in the REITs sector, from the perspective of the investor and to determine whether the effectiveness of these strategies, if any, persists through market crises. This aim may be summarised by the following two research questions. Firstly, can market timing strategies be used to earn abnormal returns in the REITs sector in general? Secondly, do the aforementioned strategies retain their ability during severely stressed market conditions?

This study investigates four market timing strategies: MA, Time Series Momentum (TSM), Modified Moving Average Crossover (MMAC), and Dual Momentum (DM) and, as such, provides a comparative analysis of market timing strategies that are seldom observed together. Further, the properties of the chosen strategies may be strongly applicable to REITs. A comparative analysis of REITs both globally and on a country-by-country basis also provides insight into the effectiveness of the selected market timing strategies in developed and emerging markets. Observing the effectiveness of market timing strategies under specific market conditions is motivated by the work of De Chassart (2002), which highlights that the success of market timing strategies may vary under bull and bear conditions. The analysis will include data over the periods covering the following market crises: (i)The GFC (ii) European Sovereign Debt crisis (ESDC)[5]; and the (iii) Covid-19 pandemic[6].

1.3 Structure of the study

The remainder of the study is structured as follows: Chapter 2 provides a critical review of empirical literature conducted on market timing, REITs in a global and South African context, as well as market timing in the REITs sector, respectively. Chapter 2 also provides empirical literature on the market timing ability of REITs' securities during market crises. Chapter 3 provides a comprehensive discussion of the data collected and methodology used to test the profitability and sustainability of the market timing strategies selected. In Chapter 4, the results of the analysis are presented and discussed. Finally, Chapter 5 provides the conclusions reached from the investigation, as well as recommended areas for future studies.

[5] The European sovereign debt crisis was a period when several European countries experienced the collapse of financial institutions, high government debt, and rapidly rising bond yield spreads in government securities. The crisis peaked between 2010 and 2012 (Kenton, 2020).
[6] The Coronavirus disease (COVID-19) is an infectious disease caused by a newly discovered coronavirus.(World Health Organization, 2021). The severity of the virus has caused millions of deaths and brought economic activity to a near halt, globally.

Chapter 2: Literature review

Chapter 2 provides a detailed discussion of local and international literature supporting the purpose of this study. A theoretical discussion introduces the market timing strategies employed in this study. Thereafter, a critical review is provided on the application of the above strategies in existing literature. Although the core focus of this study is to test market timing in REITs, a review of market timing literature done in other asset classes provides insight into the validity of existing market timing strategies. The chapter also includes reviews of factors affecting the behaviour of REITs' stock prices. Empirical evidence further evaluates the effect of including REITs in diversified portfolios. The applicability of market timing strategies in REITs are also discussed, with reference to studies done by Glabadanidis (2014) and Buttimer Jr, Chen and Chiang (2012). Chapter 2 concludes with a discussion of the performance of REITs during market crises.

2.1 Studies on market timing

As mentioned in chapter 1, investors should not be able to predict share returns in an efficient market but because of the buying and selling activity of investors, it may be possible. Market timing strategies thus provide investors with the advantage to shift between asset classes in an attempt to realise excess returns from those assets that perform well in bull markets, or consequently those that perform well in bear markets.

The most common market timing strategy is the simple MA. This rule assesses the price of the security against the average price of the same security over a selected historical period defined as the look-back period. The strategy provides a signal to buy (sell) a security once the price of that security exceeds (falls below) the average price of the security over the look-back period. Using the MA strategy thus purports that there is some future value to be derived from using past prices. It is widely used by technical analysts as part of their asset allocation rules, as it outperforms standard asset allocation (Zhu & Zhou, 2009). Asset allocation refers to the apportionment of an investor's portfolio to asset classes that are aligned to the risk and reward profile of that investor (Chen, 2020). The rationale behind this allocation entails maximising the future utility of this wealth as opposed to maximising wealth itself. In order to maximise this utility function, Merton (1969) aims to reallocate the portion of the investor's wealth held in each asset, periodically.

Two alternative market timing strategies that are commonly employed are TSM and MMAC. Derived from the MA rule, both strategies provide trading signals that are based on historical prices. However, the TSM strategy assesses the price of a security against the price of the same security at the start of a selected look-back period. The strategy provides a signal to buy (sell) when the MA over the selected look-back period changes from negative (positive) to positive (negative); i.e. a change in direction of the trend in the MA. According to Marshall et al. (2006), positions in securities tend to remain open for longer periods of time under the TSM compared to positions under the MA strategy. This alludes to the strategy performing well when the asset class under review does not exhibit large volatility.

MMAC represents a variation of the MA strategy, with a popular variation being the 50-200 days crossover strategy. The strategy is popular because it accounts for the noise found in stock prices, as Black (1986) describes. Under this strategy, the exponential MAs (EMAs) at look back periods of 50 days and 200 days are compared. The strategy signals a bullish (bearish) trend in the market when the MA calculated at 50 days exceeds (is below) the MA calculated at 200 days (Tapa, Yean & Ahmad, 2016).

Antonacci (2014) introduces an alternative market timing strategy known DM. DM attempts to time the market by using both absolute and relative momentum[7] as filters. According to Antonacci (2014), absolute momentum is an initial filter for the investor to determine the appropriate investment position. Assets that exhibit positive absolute momentum are further analysed for inclusion into the investor's portfolio. Assets that exhibit negative absolute momentum are not considered. Subsequently, the relative momentum of the selected assets are assessed. Positive absolute and relative momentum signals a buy/hold signal, whereas positive absolute and negative relative momentum signals a sell signal. Holdings are reviewed periodically against this criterion (Antonacci, 2014). In Figure 2, Antonacci (2014) provides a graphical depiction of DM using US components. At the start of each month, the investor would assess the performance of the selected passive portfolio (proxied by the S&P500) against the DM portfolio. Should the performance of the passive portfolio exceed both the performance of the DM portfolio and risk-free asset, the investor would buy or hold the passive portfolio. When the passive portfolio does not outperform

[7] Antonacci (2014) refers to TSM as "relative momentum".

the DM portfolio, and the DM portfolio does not outperform (outperforms) the risk-free asset, the investor would buy or hold an alternative safer asset (the DM portfolio). Holding an alternative safer asset may also arise when the passive portfolio outperforms the DM portfolio but does not outperform the risk-free asset.

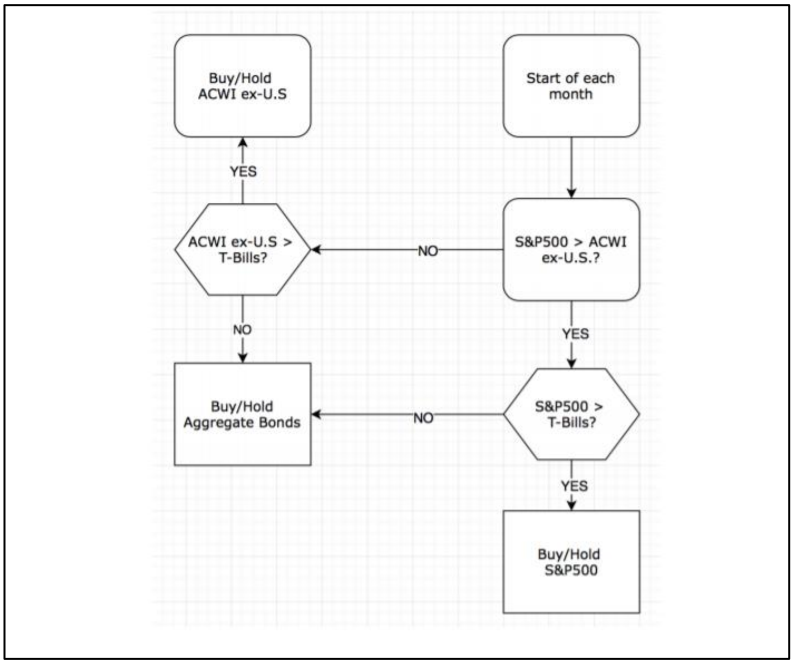

Figure 2: A graphical depiction of Antonacci's (2014) DM market timing strategy (Source: Antonacci, 2014)

Several studies have tested market timing strategies with evidence of success of these strategies relative to a buy-and-hold strategy (e.g. Glabadanidis (2014)) but some studies also provide evidence against these strategies outperforming a buy-and-hold strategy (e.g. Buttimer Jr, Chen, and Chiang (2012)).

2.1.1 Studies on the MA market timing rule

The MA rule 'smooths' out the dynamic in stock price levels by finding the average price of the stock over an observed period of fluctuations. Gartley (1935) highlights two main issues in implementing this rule. The first is the difficulty of smoothing out immaterial fluctuations to observe a trend. The second is finding an appropriate time frame of prices to observe. This is to ensure that a line of best fit can be drawn to find the most profitable results. The benefits to this rule, however, override the issues. Gartley (1935) confirms this through explaining three broad benefits. Firstly, the MA rule provides a clear direction of a trend in the observed stock prices.

Secondly, it is able to confirm the reversal in a trend. Thirdly, it attempts to remove stock price movements that are immaterial to the period under review. Although this rule has been further modified by other authors, its fundamental notion still remains relevant.

A study adapting the MA rule of Gartley (1935) was presented by Black (1986), who introduces the concept of noise trading. He assumes that the immaterial fluctuations in stock prices are attributable to factors other than fundamental information. Black (1986) explains that these fluctuations, described as ‘noise’, result in inefficiencies in the stock market that are often difficult to attribute. Therefore, stock prices will reflect both fundamental information and noise. Central to this argument is that market timing under the MA rule becomes more difficult to implement in the presence of noise. The amount of noise, as Black (1986) points out, may be substantially greater than fundamental information. While this provides liquidity and opportunities for profit generation, it does create multiple price inefficiencies. This translates directly into a riskier position, for which most investors might not have the appetite. Black (1986) holds that noise trading is more profitable when the stock is largely overvalued or largely undervalued. He further explains that the larger the overvaluation (undervaluation), the quicker the stock price will revert to its mean. The author proposes an arbitrary value of 2 to define a stock that is fairly valued. According to this arbitrary value, a stock is still fairly priced when it is overvalued by half its current price, and undervalued by less than double its current price. Therefore, a buy (sell) signal is appropriate when the price of the stock is greater than half its current value (less than double its current price). The position taken by investors will thus be subject to large information constraints.

Market timing strategies have been tested across traditional and alternative asset classes, sub-sectors of stocks, and stock indices. Papadopoulos (2017) explores the renewable energy sector as an alternative sub-sector. The choice of this sub-sector is motivated by its continuous growth in market share relative to traditional energy stocks. This growth provides the opportunity to analyse factors affecting the behaviour of renewable energy stock prices which could provide a basis for evaluating trading strategies. The sample focuses on stocks in the renewable energy sector listed in the US which have global operations. Papadopoulos (2017) examines the validity of the EMH by evaluating the performance of market timing strategies and tests the ability of the selected strategies to earn consistent profits. The author evaluates three market timing strategies. The first strategy focuses on sudden deviations in the volatility of stock returns, the second strategy focuses on sudden deviations in the trade volume of stocks, and the third strategy focuses on the MAs of security prices over a determined period. The results show that the timing strategies yield positive returns for the majority of the renewable energy sector securities examined. In ranking the effectiveness of the strategies, Papadopoulos (2017) finds that the MA strategy is the most effective strategy for stocks in the renewable energy sector. The two remaining strategies generates more negative returns than positive returns. This indicates that the indicators employed in the strategies are not the most appropriate indicators for successful market timing. The renewable energy stocks have a large capacity for future growth as an alternative asset class, much like REITs which are the focus of this study.

Ilomäki, Laurila and McAleer (2018) investigate the effects that various time frames have on the returns generated under the MA rule. The study is conducted over a period of 30 years and employs a sample of 29 companies that are listed on the Dow Jones Industrial Average (DJIA) index in January 2018. The authors also measure the volatility incurred when implementing different time frames under the MA rule, in relation to a buy-and-hold strategy. The MA rule implemented by the authors entails shifting all their holdings either to stocks or to US Treasury Bills ("T-Bills") according to the indication the rule provides. The study implements the MA rule with time frequencies varying from a MA calculated daily to a MA calculated every 100th trading day. The empirical results suggest that the use of a market timer based on the forecasts of an investor, who is a macro forecaster, is able to outperform a buy-and-hold strategy, whilst incurring lower volatility. According to the results, forecasted returns tend to be more aligned with actual returns when the MA rule is based on a less frequent time frame.

The results of applying De Chassart market timing rules have also been found to vary according to prevailing market conditions. De Chassart and Dumont (2002) assess the performance of three market timing strategies independently during bull markets and bear markets. The market timing strategies under review are namely: traditional timing, bull timing, and bear timing. Bull (bear) timing refers to the market timing strategies employed in this study, during a bullish (bearish) market phase. Historical data from the equity and money markets of South Africa are used covering a period of 74 years, from 1925 - 1998, and consists of monthly observed returns. Historical data used for the money market instruments consists of returns observed for a portfolio holding three 90-day money market instruments, with varying maturity dates. The study emphasises that market timing strategies provide potential profit based on the accuracy of the investor's forecasts. That is, forecasting ability and returns are positively correlated, while lower returns are incurred at greater levels of risk. The results indicate that of the three strategies, traditional timing provided the greatest returns, both in bull and bear market conditions. Bear timing performed better than bull timing during bull market conditions. This performance also held for the opposite conditions, i.e. bull timing performed better than bear timing under bearish market conditions. De Chassart and Dumont (2002) also highlight that bear timing strategies provide better forecasting accuracy, and therefore a greater opportunity to outperform the benchmark portfolio. When observing the results from a holistic perspective, the authors conclude that a forecasting ability of 55% is required for market timers to outperform the benchmark on a risk-adjusted basis. The empirical results also indicate that market timing during bear market conditions provides the greatest benefits to the investor. However, the benefits may only be fully realised when the investor is able to timeously identify the bear market and determine its tenure.

Faber (2007) employs a MA market timing strategy to diversify portfolio risk, and subsequently increase risk-adjusted returns. The study aims to improve risk-adjusted returns for asset classes such as commodities, REITs, the Standard and Poor's 500 index, and US Government 10-year treasury bonds. The author employs a 10-month simple MA strategy. This is a variation of the same strategy employed in a study conducted by Siegel (2002), where the strategy's effectiveness is applied to the DJIA, on a 200-day MA basis. The simple MA strategy in this study purports that an investor would invest in the non-cash asset class in the instance where the monthly price of the asset class exceeds its 10-month MA. Likewise, an investor would move to a risk-free portfolio when the monthly price of the non-cash asset class is less than the 10-month MA. The author concludes that the simple MA strategy, using the 10-month MA, mitigates the losses that investors in any of the asset classes would incur during bearish (bearish) market phases.

Zakamulin (2014) revises the study of Faber (2007) as a result of concerns that the significant excess returns are unrealistic, especially for forecasting purposes. The author investigates the historical performance of market timing strategies by looking at sample data outside their selected samples. A series of simulations are explored which take into account transaction costs and ignore set periods of review. It is found that autocorrelation is positively correlated to both MA and TSM market timing strategies. Therefore, the underlying series of returns needs to have statistically significant properties to produce a reliable buy or sell signal. According to Zakamulin (2014), the signals provided by both strategies tend to be ineffective 80% of the time, when compared to a buy-and-hold strategy. Therefore, long-term investors may be limited to marginal risk-adjusted returns because of this likelihood of underperformance.

2.1.2 Studies on the TSM market timing rule

Empirical studies often use the relative returns of securities to identify the presence of momentum. However, focusing on the returns of a single security against its own past performance (i.e. absolute returns) may provide greater predictive ability (Moskowitz, Ooi & Pederson, 2011). Moskowitz, Ooi and Pederson (2011) challenges the "random walk" hypothesis by exploring the presence of TSM that is consistent across the most liquid futures contracts, globally. The data consists of futures prices and excess returns for selected commodities, cross-currencies pairs, developed equity indices, and government bonds have been collected, for the period 1965 to 2009. Data on the positions of hedgers and speculators trading these contracts are also employed to determine the users of investors who employ TSM strategies. Following many regression analyses, the authors find that all the asset classes exhibit a strong continuation pattern in returns for the most recent 12 month period, and insignificant reversals for the next four years. This result is consistent across varying number of months used to lag returns and across varying holding periods of the assets. The overall findings of the regression suggests that the excess returns achieved under the TSM strategy exceeds the excess returns achieved by entering a passive long position in the majority of the futures contracts. TSM strategies are employed by speculators who take advantage of positive momentum returns in the first twelve months post extreme market movements. As the market moves back to equilibrium, speculators reduce their positions. Hedgers follow the opposite trading behaviour. Hedgers provide speculators, who use TSM strategies, with a premium in return for liquidity. The authors conclude that TSM strategies provide the greatest excess returns when employed during significant shocks to futures price changes and rolling returns.

Bird, Gao and Yeung (2017) evaluate the absolute and relative performance of the TSM strategy tested by Moskowitz, Ooi and Pederson (2011), and the traditional cross-sectional momentum strategy, by investigating the factors that contribute to the differences in the returns provided by these strategies. In this study, both strategies generate positive excess returns across the majority of the 24 markets employed in the sample. However, TSM outperforms the cross-sectional strategy. According to the authors, this is because cross-sectional strategies employ a contrarian investment style whereas TSM selects smaller stocks with wider spreads in past returns. Bird, Gao and Yeung (2017) find that excess returns are maximised under the TSM when stocks achieve excess return above a set level in the most recent 12 month period (i.e. “winner” portfolio). Stocks that do not achieve sufficient returns to pass this threshold are assigned to a “loser” portfolio. Under bullish market conditions, the TSM will increase (decrease) the amount of stocks in the winner portfolio in relation to the loser portfolio. The amount of stocks allocated to either portfolio remains constant under the cross-sectional momentum strategy regardless of the market state. This difference provides the opportunity for market timing.

A study conducted by Qin, Pan and Bai (2020) examines the ability of the TSM strategy to outperform a buy-and-hold strategy on stocks contained in the Shanghai and Shenzhen 300 index. “The CSI 300 Index is the stock index compiled from a sample of 300 A-shares listed on the Shanghai and Shenzhen stock exchanges. It is an indicator of the overall trend of China's stock market.” (Manqui and Shancun, 2018). Qin, Pan and Bai (2020) centre their investigation into the profitability of the TSM strategy on finding the appropriate length of historic period to observe. They purport that an optimal period of time exists which will, in turn, denote the greatest possible return generated by the TSM strategy. The study thus seeks the optimal level by first exploring different lengths of time. Once this optimal level has been found, it is decomposed in an attempt to forecast the optimal level for the next period under review. The results indicate that TSM strategies generally outperform buy-and-hold strategies under a variety of observed time periods. Profitability is largely dependent on the market cycle in which the strategy is implemented, as well as the general outlook of investors. This observation is consistent with De Chassart and Dumont (2002) who also find that the results of market timing strategies are different under bull and bear markets. The authors conclude that a predictive model should be tailored to the asset class under review to determine its performance under the TSM strategy.

Section 2.1.1 and earlier studies in this section have highlighted that momentum is typically observed over a number of days or months. However, O’Hara (2015) highlights that the increased use of technology in trading has significantly increased the volume of trading. Against this backdrop, Li, Sakkas and Urquhart (2021) examine TSM over an intra-day frequency as well as the source of any excess returns attributable to this variation of TSM. The authors conduct this study over a 18 year period, using the half-hourly returns of stock indices in developed markets. The findings reveal that significant momentum exists under this strategy and that the first half hour of the trading day is able to predict the returns of the last half hour of the trading day. The findings further reveal that volatility and returns are significantly greater in the first half hour of the trading day than in the last hour. This is attributable to investor's reaction to overnight information affecting the stocks under observation (Li, Sakkas & Urquhart, 2021). The analysis also reveals that TSM negatively correlated to liquidity. This relationship is explained by liquidity shocks that arise from investors' reaction to overnight information at the beginning of the trading day. According to the authors, investors who typically provide liquidity will sell off their positions near the end of the trading day since the market is most liquid. Investors who do not trade frequently would absorb this liquidity shock by assuming these positions.

2.1.3 Studies on the MMAC market timing rule

Tapa, Yean, and Ahmad (2016) employ a MA crossover strategy with the aim to realise greater excess returns in comparison to the returns realised under a standard MA strategy. Their approach extends the standard MA strategy by adding additional trading rules. The additional trading rules include a minimum holding period, as well as stop loss parameters. It should be noted that the standard MA crossover strategy only accounts for an entry point and an exit point. They apply this modified approach to stocks listed on the Malaysian stock exchange, using daily returns over the period 2000-2014. The evidence suggests that all variations of the MMAC strategy employed in their study outperform a traditional buy-and-hold strategy. They conclude that past trends may be used to predict future performance.

Anghel (2013) investigate whether consistent excess returns may be achieved in the Romanian stock market by using a MA crossover rule instead of a buy-and-hold strategy. The author motivates that the application of this strategy will provide insight to the efficiency of a stock market that is less matured compared to US and South Korean stock markets. To this extent, daily data of liquid stocks in various sectors are used in this study covering the period 2001 to 2011. The stocks are listed on the New York Stock Exchange (NYSE), Korea Stock Exchange (KRX), and the Bucharest Stock Exchange (BVB). The results indicate the MA crossover rule does not yield significant excess returns over the buy-and-hold strategy in both bull and bear market conditions. During bullish market conditions, the strategy is able to generate consistent but insignificant excess returns. According to Anghel, the loss to the investor is greater during bearish market conditions that existed in the latter part of the sample period because of the market state and transaction costs incurred. The trading strategy should thus need to be adapted to the current market conditions when it is implemented.

The ability of the MMAC strategy to outperform a buy-and-hold strategy is explored by Patari and Vilka (2014), from a Finnish perspective. The strategy is applied to the daily closing prices of both the OMXH25[8] as well as the individual stocks underlying the index using varying lengths for both MAs. The authors argue that individual stocks are more volatile than indices and therefore there are more opportunities to earn excess returns. This argument is further motivated by the Finnish market being defined by low liquidity (Patari & Vilka, 2014). The authors identify bullish and bearish periods in the Finnish market to determine the relative performance of the index and portfolio of individual stocks to the buy-and-hold strategy. In contrast to the findings of Anghel (2013), the findings of Patari and Vilka (2014) suggest that both the portfolio of individual stocks and OMXH25 outperforms (underperforms) the buy-and-hold strategy during bearish (bullish) market conditions. This finding is applicable to both institutional and individual investors for all variations of the MMAC strategy. However, higher transaction costs and tax implications reduces the hedge advantage for individual investors during bearish market conditions.

2.1.4 Studies on the DM market timing rule

The price momentum effect provides investors with opportunities to generate abnormal returns. However, this anomaly is not fully explained by current models such as TSM and MA. Antonacci (2017)[9] introduces the framework of DM by investigating the outcome of combining absolute and relative momentum. The author explains that an investor has two choices under the DM strategy. In the first scenario, an investor will elect to invest in a risky asset when both absolute and relative momentum are positive. In the second scenario, an alternative proxy security when the absolute momentum is negative. Antonacci (2017) maintains that the inclusion of a safer alternative proxy security provides the portfolio with diversification benefits. Each respective type of momentum also contributes to the diversification benefit. Correctly identifying positive absolute momentum

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[8] OMX Helsinki 25 (OMXH25) is the Helsinki Stock Exchange leading share index weighted by market value. The index consists of the 25 most actively traded stocks on the Helsinki Stock Exchange (Nasdaq.com, 2021).
[9] The first version of this study is 18 April 2012.

eases downside deviation while using the trend persistence to achieve excess returns. The combination of absolute and relative momentum further increases excess returns. The findings of this study suggests that a DM strategy can be successfully applied to the real estate and equity sectors. It is also able to persist through credit risk and severe economic stress.

Tonnessen (2018) investigates the theoretical and practical validity of the DM strategy of Antonacci (2014), by replicating the strategy from a Norwegian perspective. In order for Norwegian investors to replicate this strategy, the author replaces the monthly returns of the US equivalent components of Antonacci (2014) strategy with monthly returns data of the Oslo Stock Exchange total return index, the Norway government bond index, and the NIBOR 3 month bill. The study is conducted over the period 1996-2018 to observe the effectiveness of this strategy during prominent crises such as the dotcom[10] bubble and the GFC. The results presented by Tonnessen (2018) indicate that the DM portfolios constructed in this study consistently outperforms the buying and holding any of the Norwegian indices by providing greater risk-adjusted returns and reducing the aggregate risk of the portfolios. In line with the price momentum anomaly, this strategy maximises returns in bull markets and signals a shift to a portfolio of bonds in bear markets. A key observation is that this strategy results in a higher compounding rate since dual momentum portfolios have to recoup less losses than buy-and-hold portfolios during periods of market recovery. Tonnessen (2018) concludes that this strategy provides the greatest excess returns over longer periods of time than shorter periods of time.

2.1.5 Studies on market timing rules used in non-equity asset classes

Although many studies on market timing focuses on equity securities, market timing may also be applied in non-equity asset classes. One such asset class is fixed income. Since REITs have properties akin to both equity and fixed income (Carstens, 2018), studying market timing strategies in fixed income may provide further insight into constructing market timing strategies to predict REITs returns. Duyvesteyn and Martens (2013) prove that factors used to time developed government bonds returns may also be applied to time returns of emerging market (EM) government bonds. The factors used by the authors to form an active duration strategy include

[10] "The dotcom bubble was a rapid rise in US. technology stock equity valuations fueled by investments in Internet-based companies in the late 1990s. Equities entered a bear market after the bubble burst in 2001, causing many internet companies to go bust." (Hayes, 2019).

bond momentum, equity momentum, and term spread. The results of the study find that returns in bond momentum are inversely related to returns in equity momentum. That is, under bearish (bullish) market conditions, investors tend to shift their portfolios from equity (bonds) to bonds (equity). The term spread assists in predicting the magnitude of bond excess returns (Duyvesteyn and Martens, 2013). Further, the same factors applied to developed market government bonds provides similar excess returns to EM government bonds, suggesting that there is significant correlation between the two bond types. The authors conclude that the active duration strategy is successful for both developed market government bonds and EM government bonds.

In another fixed income study, Bektic and Regele (2017) investigate the applicability of a simple MA strategy in the US corporate debt market. As observed earlier in this chapter, this strategy is also employed by Zhu and Zhou (2009) and Faber (2007) from an equity perspective. Bektic and Regele (2017) use monthly return data for high yield (HY) and investment grade (IG) US corporate bonds in this study. The findings suggest that excess returns are positively correlated with both the volatility of the underlying portfolios as well as the overall market volatility. This suggests that excess returns can be achieved more consistently for HY bonds than for IG bonds under this strategy because of the increased volatility displayed by HY bonds. In line with the findings of Zhu and Zhou (2009), Bektic and Regele (2017) find that some predictive value of future returns can be derived from analysing past bond returns.

Prominent market crises have proven that investors view gold as a safe haven asset. Research done by Baur and McDermott (2010) provides evidence that gold is an effective hedge and diversification instrument in times of market. However, research has been done to test whether market timing strategies can be effectively applied to this commodity. Baur et al. (2020) investigate the efficiency of the gold market by attempting to use market timing strategies to discredit a buy-and-hold strategy. Monthly returns are used to construct technical market timing signals based on MAs and momentum, respectively. Fundamental and economic indicators that determine the movement in gold prices are also used to form market timing signals. Initially the authors find that technical and fundamental market signals produce excess returns greater than a buy-and-hold strategy. However, they argue that analysing market timing signals on a single set of past returns may falsely render the signal as superior, i.e. data snooping. After controlling for data snooping, Baur et al. (2020) find that none of the strategies outperform a buy-and-hold strategy on a statistically significant basis. Therefore, according to this study, the gold market is efficient.

Almudhaf and AlKulaib (2017) oppose market timing in the precious metals sector. The authors argue that significant excess returns in this sector are outliers that result from extreme market volatility. Assuming that most investors are risk-averse, their assumption of a normal distribution of returns in this sector would lead to excess returns by chance or significant losses as a result of predicting the incorrect trend direction. However, the frequent occurrence of extreme swings in volatility provides merit for testing the applicability of market timing strategies against a buy-and-hold strategy in this sector. The main finding of this study suggests that a buy-and-hold strategy outperforms any market timing strategy. The authors attribute this conclusion to investors underestimating the volatility of precious metal prices. Many of the excess returns and losses are concentrated at random days, hence investors find that the amount of observed outliers far exceed the amount expected outliers. Although investors may successfully identify these days of concentration, the authors argue that investors are not able to identify them in timely manner.

2.2 Studies on REITs and the impact of market crises on REITs

2.2.1 Studies examining the risk and return characteristics of REITs

Numerous studies have examined the risk and return characteristics of REITs in order to understand their diversification role in a portfolio. This literature is briefly reviewed before focusing on market timing rules in REITs so as to better understand the characteristics of this asset class and the major research which has been done on this asset class. Stephen and Simon (2005) investigate the effects of including REITs in a portfolio consisting of multiple asset classes. In particular, the authors evaluate the risk and return outcomes of allocating REITs in an optimal portfolio, over both short- and long-term holding periods. An observation period spanning from 1980 to 2002 is employed. The approach to this evaluation is comparative. For the same level of return, the first comparison is drawn between portfolios on the efficient frontier that include an allocation to REITs and portfolios on the efficient frontier that do not include an allocation to REITs. For the same level of risk, a second comparison is drawn between the former and latter portfolios. It is found that REITs provide greater diversification benefits at the lower end of the efficient frontier (i.e. when standard deviation is lower) than at the higher end of the efficient frontier. Returns are also greater with the inclusion of REITs in the portfolio. The results are mostly consistent over short- and long-term holding periods. A significant point made in this study relates to the inclusion of both physical real estate and REITs in the portfolios under review. The authors maintain that the benefits provided by both assets will become redundant to the long-term investor. That is, the behaviour of the long term returns of REITs are akin to the returns behaviour of physical real estate whereas the behaviour of short term returns is akin to financial securities.

A study conducted by Mull and Soenen (1997) also investigates the benefits of including US-listed REITs as an asset class within an international investment portfolio. The authors created portfolios consisting of domestic stocks and bonds, and US-listed REITs, from the perspective of every G7 country. Conclusions are drawn from monthly data for all three asset classes over the period 1985-1994. The results indicate that US-listed REITs provide limited diversification and return benefits in relation to domestic stocks and bonds for investors based in the majority of G7 countries. The authors attribute this poor performance to the differing trading conditions between US-listed real estate and the respective foreign stock markets. These differences include differing economic conditions, poor currency performance relative to the US dollar, and poorly performing US-listed REITs. Differences in market conditions may not provide the most accurate delineation of risk and return, and as a result, may distort comparability.

Aguilar, Boudry and Connolly (2018) investigate the factors that influence the efficiency of REIT prices specifically. They observe that shareholding in REITs by active institutional investors significantly contribute to the efficiency in the pricing of REITs, whereas ownership of REITs' shares by passive institutional investors neither increased nor decreased pricing efficiency. The authors also find that REITs are already priced efficiently when they are listed on large cap indices. In contrast, REITs that are listed on mid-cap indices are attractive to growth investors. This indicates short term inefficiency and long-term efficiency. The research presented by Aguilar, Boudry and Connolly (2018) also concludes that the extent of coverage by REIT analysts has a positive relationship with the pricing efficiency of this asset class. Their findings are consistent with research presented by Downs and Güner (2000). The last observation concludes that the investment and divestment activity of REITs also has a positive relationship with REITs' share prices.

A study by Chaudry, Maheshwari, and Webb (2004) explores the idiosyncratic risk inherent in REITs. The authors chose REITs because of the diversification and tax benefits borrowed from the equity and fixed income properties of REITs. Further, they highlight that forecasting the returns on REITs is similar to forecasting the returns on normal stock portfolios. They further motivate the choice of asset class by stating that the performance of the underlying assets are exposed to bullish and bearish markets. Bullish and bearish trends run in tandem with the returns generated by securities such as REITs. During a bullish trend, real estate prices will rally, increasing the distributable returns owed to REIT investors. Although investors may profit from short selling in a bearish trend, REIT investors are often long-term investors. Hence, the distributable returns will diminish when the real estate sector is in a bearish trend. The changes in the economic trend thus gives rise to sector inefficiencies. As mentioned in Chapter 1, inefficiencies can give rise to opportunities for successful market timing strategies. The methodology decomposes the idiosyncratic risk of REITs from the perspective of REIT investors, by using a regression model. The results of the regression analysis indicates that leverage, price performance, liquidity, capital, and earnings volatility are significant determinants of idiosyncratic risk. However, the size of REITs do not contribute significantly to this risk. According to Chaudry, Maheshwari, and Webb (2004), these observations provides REITs investors with guidance when seeking to diversify mixed-asset portfolios by including REITs. Therefore, the authors conclude that examining the idiosyncratic risk of REITs is equally as important as examining the risk-return relationship for normal stock portfolios.

Ro and Ziobrowski (2009) evaluate the performance of REITs by comparing REITs that manage a single property type with REITs that manage a diverse portfolio of properties. The data in this study consists of monthly returns for both groups for the period 1997-2006. The authors construct value- and equal-weighted portfolios for both diversified REITs and single property type REITs, respectively. Under the value-weighted style, the portfolios are constructed according to the proportions of the market capitalisation of the underlying REITs. The equal-weighted portfolios assist in eliminating any size effects created by securities that account for extremely large portions of the portfolio. Both the Capital Asset Pricing Model and the Carhart (1997) four factor model implemented in this study indicate that REITs with a diverse portfolio of properties outperform single property type REITs. This conclusion holds for various lengths of observations, as well as on a value- and equal-weighted basis. Although specialising in one type of property should provide superior information from which to produce significant returns, it may not provide returns in a consistent manner. The conclusion reached by the authors is consistent with the general rule of diversification.

In a South African context, Makatsane (2018) also compares the performance of specialised industrial REITs with the performance of REITs with diversified portfolios. However, the approach taken to compare and analyse the performance of both is qualitative (i.e. a case study method) and not quantitative. Makatsane (2018) considers macroeconomic variables such as the state of the economy and sector performance, as well as microeconomic variables such as the size of the REIT and its gearing ratio. Alongside the analysis of the performance of industrial REITs, Makatsane (2018) evaluates the impact of the growth in e-commerce on these specific REITs. This adds to the robustness of the study and recognises the effects that technological influences have on the performance of securities in this sector. The results of the interviews provide a consensus conclusion. Outperformance of either type of REITs is dependent on a combination of macro- and microeconomic factors, with economic conditions and domestic political climate being the most important contributors to the performance of REITs. The interviews also provided meaningful conclusions for the secondary study focusing on the effect of e-commerce. Generally, respondents reasoned that the strong rise of e-commerce has created a large demand for warehouse spaces close to modes of international transport hubs, and a subsequent decrease in demand for retail space. This is especially notable in the South African context, since SA acts a major distribution hub for the African region. In turn, performance of specialised industrial REITs will receive positive momentum as the demand continues to rise.

2.2.2 Studies evaluating the impact of market crises on REITs

Huerta, Egly, and Escobari (2015) investigate the effects of the GFC on the returns and volatility of REITs together with the role of investor sentiment on the returns generated by REITs. The study is conducted in the US and includes the period of the formation of the house-pricing bubble, the bust, as well as the market recovery period following the crisis. The length of the crisis extends from October 2008 to July 2009. Huerta, Egly, and Escobari (2015) observe that the crisis restricted the ability of REITs to raise funds through debt and equity markets. The liquidity of REITs was further constrained by the inability of banks to provides credit line facilities. As a result, REITs could not meet their mandatory dividend payments or grow their portfolios significantly. The authors use autoregressive models to assess the effects of the crisis on the variability of REITs returns and use weekly surveys to measure the sentiment of individual and institutional investors. The results indicate that REITs' returns deteriorated significantly during the crisis while their volatility increased significantly. A combination of liquidity constraints and increased volatility caused investors to view REITs as a risky asset class. Huerta, Egly, and Escobari (2015) also find that negative shocks to the economy have a larger impact on volatility in comparison to positive shocks. Similar to Boudry et al. (2012), the authors observe that REITs' securities behave more like equity than bonds during times of market crisis, since bond factors have insignificant explanatory power on the variability of the returns of REITs. From a behavioural finance perspective, the authors find that institutional investors are able to influence the returns of REITs' securities more significantly during the crisis than individual investors because of the size of their capital. This finding is consistent with the findings of Boehmer and Kelly (2009), cited in section 2.2, who investigated pricing efficiency in the general equity market. Liquidity constraints are thus viewed by investors as a negative indicator of the future performance of REITs. As a result, Huerta, Egly, and Escobari (2015) conclude that investors prefer to shift their portfolios into lower risk investments at the expense of superior returns during a market crisis.

Chang and Chen (2014) investigate the extent of contagion in global REITs markets during the GFC. The authors select this crisis because its continued influence post the crisis provides insight into the effectiveness of international diversification benefits for REITs investors, given the existence of contagion. Daily returns data of REITs located in North America, Europe, Africa, the Middle East, Asia, and the Pacific are obtained from Bloomberg for the period 2006 to 2010. Correlation analysis of the daily returns of the selected REITs markets indicate that positive correlation exists for a large part of the between -country sample, in general. Chang and Chen (2014) define market panic as sudden changes in volatilities and use an algorithm which identifies two occurrences of market panic over the period under review. The two occurrences are used to analyse the extent of contagion. The analysis of the first occurrence indicates that there is a significant increase in the contagion effect from the US REITs market to the Asian REITs markets. Therefore, US REITs investors who included Asian REITs in their portfolio would have suffered significant losses during the crisis. The analysis further indicates that the returns of European REITs are more sensitive to market panic than the returns of Asian REITs. US REITs and European REITs tend to have negative correlation but still experience negative returns induced by the crisis. The authors conclude that contagion is found across all REITs markets but is most significant in Asian REITs markets. Therefore, Chang and Chen (2014) suggest that REITs investors should consider asset classes other than REITs during a market crisis.

Abuzayed, Al-Fayoumi and Bouri (2020) investigate whether REITs' securities can provide downside protection in a European stock portfolio. The study tests the presence of this hedging ability particularly during the periods that include the GFC and the ESDC. Following the approach of Liu et al. (2019) in section 1.2, Abuzayed, Al-Fayoumi and Bouri (2020) tests the hedging ability of European REITs' securities by analysing the correlation between European REITs' securities and selected non-REIT equity securities. The authors motivate that insight into the relationship between the two security-types during times of market crisis may provide effective trading strategies for hedgers and provide an optimal asset allocation framework for REIT investors seeking downside risk protection. The authors find that the positive correlation between the two security types increases significantly during both crises. Therefore, a stock portfolio including REITs loses its diversification benefit during both crises. Abuzayed, Al-Fayoumi and Bouri (2020) also observe that to maintain their current risk exposure, investors should review and rebalance their positions in REITs more frequently than other asset classes. This is to ensure that the most appropriate hedge ratio is applied to the portfolio.

Unprecedented restrictions to economic activity have severe impacts on rental revenue earned by REITs (Milcheva, 2021). Milcheva (2021) investigates the effect the Covid-19 pandemic had on the risk-return relationship of US REITs' securities relative to Asian REITs' securities. The author motivates that the REITs sector is resilient during market shocks and have a low correlation to equity during normal market activity. This low correlation is also observed by Lee and Stevenson (2005) and de Klerk (The South African Institute of Tax Professionals, 2019). However, lockdown restrictions imposed by many governments as a result of Covid-19 have caused businesses to shut down. As a result, many REITs lost significant rental income during this period. Milcheva (2021) argues that a significant loss in rental income opts REITs investors to revise their valuations of REITs securities because of the increase in the riskiness of these securities. In order to assess the impact of the Covid-19 pandemic, Milcheva (2021) formulates a factor model to assess the sensitivity of US and Asian REITs securities to a risk factor that is based on the daily Covid-19 infection rate for each region. The regression analyses provide many notable points. A rise in the infection rate translates into rapid declines in the returns of REITs in both regions. However, the decline in returns is more pronounced in the US REIT market than in the Asian REITs market. The author finds that this is attributable to the response of the different sub-sectors of REITs to the pandemic. US REITs' securities had large variations in performance depending on the specialisation of the REITs whereas Asian REITs' securities exhibited similar trends in performance regardless of their subsector. Milcheva (2021) explains that this behaviour is considered normal for Asia, since this region has previously experienced similar infection outbreaks. The results also indicate that the performance of US hotel REITs are most sensitive to an increase in Covid-19 infections, whereas the same is true for Asian REITs specialising in office real estate. Asian investors are thus able to implement trading strategies more easily to limit their downside risk exposure when compared to US investors.

2.3 Studies on market timing in REITs

While market timing strategies have been researched across many asset classes, very little research has focused on implementing market timing strategies in REITs explicitly. Glabadanidis (2014) explores the market timing advantage of the MA strategy over the buy-and-hold strategy, using both individual REITs and REIT indices. The study is conducted in the US. In line with the typical 30 year-length of buy-and-hold strategies for the underlying assets, the author observes returns for the individual REITs and the subsequent indices over the period January 1980 to December 2010. The author specifically analyses value- and equal-weighted REIT indices. The rationale corroborates the study conducted by Ilomäki, Laurila and McAleer (2018), through motivating that monthly return observations provide better forecasting accuracy than daily return observations. The author motivates the selection of individual REITs because the underlying assets may be allocated to a specific use. This increases the accuracy of the observed returns. The results of the regressions and simulations indicate that the MA strategy outperforms the buy-and-hold strategy, both for the value- and equal-weighted indices. The author maintains that excess returns persist even after accounting for investor behaviour and subsequent investment risks. The model implemented by Glabadanidis (2014) may be used by individual investors since it relies on a less frequent observed time frame. The results of the effectiveness of the MA strategy in individual REITs are closely aligned to the results observed for REIT indices. The author observes that the risk is reduced and that excess returns may be consistently achieved by implementing the simple switching strategy. Glabadanidis (2014) explains that this strategy signals to invest in a portfolio of cash when the price of REITs index breaks below the MA for the period under review. Similarly, an investor would invest in the value- or equal-weighted REITs portfolio in the instance where the price breaks above the MA for the period under review. The study does not fully account for outliers or unobserved fluctuations which could enhance the predictive ability of the strategy.

As mentioned in chapter 1, the EMH put forward by Fama (1970) suggests that investors reach the same consensus about market information and therefore are not able to achieve superior returns. However, the introduction of new security-types such as REITs could detract from this perceived efficiency. Liu et al. (2019) evaluates whether the Hong Kong REITs market is efficient by investigating the correlation between changes in the efficiency of REITs market to changes in the efficiency of the stock market and real estate market, respectively. The authors employ the Hurst exponent to assess the efficiency of the REITs market. Based on this method, they find that price changes in Hong Kong REITs do not follow a random walk but rather display long term price persistence. Although still inefficient, the Chinese REITs market moves closer to weak form efficiency as it become more mature and legislative liquidity requirements are imposed. The authors also find that the correlation between this REITs market and the stock and real estate markets are low. This is because there are no clear cycles observed in either the stock and real estate markets in Hong Kong, in relation to the predictive trends identifiable in its REITs market (Liu et al., 2019). The authors use these results as motivation for investors to time the market using technical analysis.

To the knowledge of this author, the only other study that has explicitly investigated market timing in REITs is that of Buttimer Jr, Chen, and Chiang (2012). However, rather than focusing on the use of REITs to move in and of cash to outperform a buy-and-hold strategy, the authors examine the profitability of REITs, and subcategories of REITs, by testing the manager's ability to move in and out of the physical underlying properties in which the REITs are invested. The authors note that the REIT sector is growing and that the possibility for market timing ability may be a continuous study, even if the underlying properties may not be as liquid as securities found in stock index funds. The methodology followed includes multiple regression analysis and the implementation of a multifactor model with variations constructed by the authors. The authors also test whether excess returns and market timing ability continue to exist when accounting for macro factors in their model. As expected, the subcategories of REITs perform differently amongst one another. Notably, office REITs are able to signal undervalued properties, whereas all other subcategories exhibit poor market timing ability. Therefore, Buttimer Jr, Chen, and Chiang (2012) do not believe that equity REITs are able to outperform index funds.

2.4 Chapter summary

A comprehensive analysis of global and South African financial literature was undertaken in this chapter, and has highlighted that market timing has been extensively researched across many sectors. Generally, strategies such as MA and TSM enjoy preference because investors have been able to use them successfully. Under-researched strategies, such as MMAC, and the formation of new strategies, such as DM, provides alternative possible avenues for predicting excess returns. However, some research also indicate that market timing strategies may not always be applied successfully. This may be attributed to a range of factors from incorrect estimation of market volatility to buy-and-hold strategies providing more consistent excess returns in certain sectors.

As a starting point for evaluating the effectiveness of market timing REITs, theoretical and practical discussions of four market timing strategies were provided. The findings suggests that the MA strategy appears to be the most universal strategy, since it is successfully applied to sectors ranging from renewable energy (Papadopoulos, 2017) to fixed income (Bektic & Regele, 2017). Since MMAC is based on the original MA, the same conclusion has been reached for this strategy. While relative momentum provides key insights into the performance of an asset, studies done by Bird, Gao and Yeung (2017) and Moskowitz, Ooi and Pederson (2011) find that the TSM which focuses on absolute momentum, are able to generate excess returns more consistently during market shocks than relative momentum market timing strategies. The seminal work of Antonacci (2014) introduced the DM strategy, which combined absolute and relative momentum in attempt to further explain the price momentum effect inherent in the real estate and equity sectors. Tonnessen (2018) confirmed the validity of the DM strategy by replicating it from a Norwegian perspective.

Although momentum in returns are the core of the market timing strategies employed, many studies found that the success of these strategies depended on investors’ perception of market volatility as well as selecting the appropriate time frame to observe returns. The analysis highlighted that few studies have explicitly focused on market timing in REITs. However, the few studies that were found have opposing findings about the success of market timing in REITs. Chapter 3 introduces the method used in this study.

Chapter 3: Research methodology

Chapter 3 presents the methodology followed to answer the research questions outlined in section 1.3. First, the research design is discussed. Second, the graphical and statistical methods used to describe the normality of the transformed data are explained. Thereafter, a clear outline of the market timing rules that are implemented in this study is provided.

3.1 Research design

This paper follows a quantitative research approach. According to Creswell (2015), a quantitative method entails the collection of data and quantification of relevant variables by using statistical methods. Combining this data with information that can be interpreted forms the basis to provide generalised principles for future research. The purpose of this study is to investigate the effectiveness of market timing strategies in the REITs sector, from the perspective of the investor and to determine whether the effectiveness of these strategies, if any, persists through market crises.

More generally, quantitative studies are utilised for the evaluation of market timing strategies. Although little research has been done on market timing in REITs, the studies of Glabadanidis (2014) and Liu et al. (2019) reviewed in Section 2.3 both follow a quantitative approach to test whether market timing strategies have the ability to earn abnormal returns in the REITs sector.

3.2 Data adjustments and descriptive statistics

3.2.1 Lognormal distributions

Since security prices are used to determine monthly returns, it is important to transform the data to a lognormal distribution. This is because security prices cannot be negative. The monthly returns of the REITs indices used in this study are thus calculated by using the follow formula:

$$R_i = \ln\left(\frac{P_t}{P_{t-1}}\right) \text{ where } t \geq 1 \qquad (1)$$

where P_t is defined as the security price at time *t*.

3.2.2 Descriptive statistics

The descriptive statistics presented are intended to provide an overview of the returns data. The statistical measures that are presented are: (i) Jarque-Bera (JB), and (ii) Shapiro-Wilk (SW).

(i) Jarque-Bera

Applying the JB test provides insight into the normality of the data set, with the aim of making comparable inferences within the subsets of the data set (Mantalos, 2011). This is particularly significant in the context of this study since REIT indices are at different stages of maturity in relation to one another. The JB test is based on kurtosis and skewness and is calculated in the following manner:

$$\text{JB} = n\left(\frac{\left(\sqrt{skewness}\right)^2}{6} + \frac{(kurtosis-3)^2}{24}\right) \qquad (2)$$

where n = sample size (Beau, 2019).

Using the JB test to make inferences about the normality of the data set is largely dependent on the sample size. Skewness and kurtosis is derived from the results from section 5.1 Descriptive statistics below. As a general rule for this study, the data is assumed to be normally distributed if the p-value of the statistic is greater than 0.05. Similarly, the data is assumed not to be normally distributed if the p-value of the statistic is less than 0.05.

(ii) Shapiro-Wilk

Alongside the JB test, the SW test is commonly used to test for deviations from normality in a data set (Das & Imon, 2016). For this reason, it is used to confirm the conclusion on normality as indicated by the JB test above. The SW test is calculated in the following manner:

$$\text{SW} = \frac{\left[\sum_{i=1}^{n} a_i Y_i\right]^2}{\left[\sum_{i=1}^{n} (Y_i - Y)^2\right]} \qquad (3)$$

and $0 \leq SW \leq 1$

where a_i represents the weights from the sample size and Y_i represents a vector of the ordered observations (i.e. index returns over the sample period) for a normal distribution. *Y* represents the mean of the specific series of returns. It is crucial to remember that this test only indicates that the significance (or insignificance) of the deviation from normality and that it does not assess the level of normality itself.

3.3 Methodology for implementing market timing rules

The studies reviewed in chapter 2 mainly focus on the effectiveness of one market timing strategy within a specific sector, asset class and geographic market. However, this study focuses on multiple market timing strategies across many geographic markets for a single asset class. Therefore, a detailed discussion of the approach used to test the effectiveness of all four market timing strategies is thus imperative to understanding their implementation in this study.

3.3.1 Calculation of the MA market timing rule

Following Han et al. (2013), the MA is calculated as follows:

$$MA_{t.n} = \frac{P_{t-n+1}+P_{t-n+2}+\cdots+P_{t-1}+P_t}{n} \tag{4}$$

where $MA_{t.n}$ is the moving average on day *t* of length *n* and P_t is the price level of the index on day *t*. Many studies of the MA market riming rule, such as Han et al. (2013), indicate that there is no set time period over which to measure a MA (i.e. the value of *n*). However, there does seem to be consensus around the use of 10, 20, 50, 100, and 200-day periods amongst some of the studies. Ideally, the MA in this study would be calculated for all five periods. However, the data used in this study follows a monthly return interval. Therefore, the MA is rather calculated at intervals ranging from 1-6 months, since these intervals are the closest approximation to the MAs calculated at the above daily intervals.

Similar to Glabadanidis (2014), the monthly closing price of the REIT index is compared to the MA for that period to determine whether the investor should buy or sell the security. The MA rule provides a signal to buy (sell) a security once the price of that security exceeds (falls below) the average price of the security for the month. When the signal switches from a buy (sell) to a sell (buy), the investor would switch from the REIT index to cash (and vice versa) the following month. The return generated by the strategy is computed by the positive difference between the previous period's switch and the current period's switch. The returns can be expressed as follows (Glabandinis, 2014):

$$\tilde{R}_{t,n} = \begin{cases} R_t & if\ P_{t-1} > MA_{t-1.n} \\ r_{ft} & otherwise \end{cases} \tag{5}$$

3.3.2 Calculation of the TSM market timing rule

The TSM strategy assesses the price of a security against the price of the same security at a certain point in time. The strategy provides a signal to buy (sell) when the MA over the selected period changes from negative (positive) to positive (negative); i.e. a change in direction of the trend in the MA. The MA is calculated as per equation 4. The following equations, adapted from Marshall et al. (2017), are used to determine the appropriate trade signal:

$$TSM_{t,n} = P_t - P_{t-n} > 0 \text{ Buy signal} \tag{6}$$

$$TSM_{t,n} = P_t - P_{t-n} < 0 \quad \text{Sell signal} \tag{7}$$

where a buy signal (sell) is created when the current price of the REIT index moves above (below) its historical price. In the instance that Equation 6 applies, an investor would rotate from holding the REIT index to holding a portfolio proxied by a portfolio of domestic T-bills. Central to the implementation of the TSM rule is the principle that the signal given by this rule relies on the change in direction of the MA itself (Marshall et al., 2017). Given this argument, it can be mathematically proved that the buy signal under the TSM rule equates to the change in direction of the MA, that is:

$$MA_{t.n} - MA_{t-1.n} = \frac{P_t - P_{t-n}}{n} \tag{8}$$

$$P_t - P_{t-n} = n * MA_{t.n} - MA_{t-1.n} \tag{9}$$

Therefore when $n * (MA_{t.n} - MA_{t-1.n}) < 0$ moves to $n * (MA_{t.n} - MA_{t-1.n}) > 0$, a buy signal is formed (Marshall et al., 2017).

Consistent with the periods reviewed under the MA rule and following Han et al. (2013) the TSM is also calculated at intervals ranging from 1-6 months, since these intervals are the closest approximation to the MAs calculated at the above daily intervals.

3.3.3 Calculation of the MMAC market timing rule

The 50-200 days crossover strategy variation is applied to the MMAC rule used in this study. Under this strategy, the EMAs at 50 and 200 days are compared. According to Maverick (2020), EMAs place more emphasis on recent price data than the canonical MA and are designed to observe data over absolute time frames, such as the 50-200 day period. In order to place a greater weighting on recent data, a multiplier is included as follows:

$$k = \frac{2}{n+1} \tag{10}$$

$$EMA_t = P_t * k + EMA_{t-1}(1-k) \tag{11}$$

where: k is the weighted multiplier and EMA_t is the exponential MA on day t (Maverick, 2020).

The crossover strategy signals a bullish (bearish) trend in the market when the exponential MA calculated at 50 (200) days exceeds the exponential MA calculated at 200 (50) days. In the context of this study, the result of this calculation indicates the following:

$$EMA_{50} > EMA_{200} = Buy\ or\ hold\ REIT\ index \tag{12}$$

$$EMA_{200} > EMA_{50} = Sell\ REIT\ index \tag{13}$$

This variation is also used by Tapa, Yean, and Ahmad (2016). In the instance that Equation 12 applies, an investor would rotate from holding the REIT index to holding a portfolio proxied by a portfolio of domestic T-bills. Equation 4 also applies to the calculation of the MA under this rule, since this rule is rooted in the simple MA market timing rule discussed in Section 3.3.1.

3.4 Calculation of the DM market timing rule

Following the approach of Tonnessen (2018), the DM market timing rule of Antonacci (2014) is replicated in this study. The DM market timing rule is a relatively new rule when compared to the three rules presented above and has very detailed steps in its implementation. These are outlined below.

3.4.1 Look-back period

Again, the look-book period is crucial to identifying dual momentum in the changes of historical REITs' stock prices. Antonacci (2014) maintains that a 12-month look-back period is used in many market timing studies as it maximises excess returns. This conclusion is consistent with the findings of Moskowitz, Ooi and Pederson (2011) and Bird, Gao and Yeung (2017), reviewed in Chapter 2, who find that excess returns achieved under the TSM market timing rule are also maximised when using a 12-month look-back period. A 12-month look-back period allows for the MA to be observed over the long-term period only, which adds to the reliability of test results.

Since this is a replication of the DM market timing rule of Antonacci (2014), a 12-month look-back period is used in this study. Using the same look-back period is further motivated by an attempt to mitigate data snooping and to acknowledge that it is optimal period for implementing long-term strategies[11], as Antonacci (2014) and Tonnessen (2018) confirmed. The following formula is used to calculate the look-back period under this rule:

$$R_{i,t=k} = \frac{P_{i,t=0} - P_{i,t-k}}{P_{i,t-k}} \tag{14}$$

where $R_{i,t=k}$ represents the return on the REIT security (denoted by *i*) in time period *t* with look-back period *k*, is calculated by subtracting, $P_{i,t=0}$ represents the current price of the REIT security and $P_{i,t-k}$, represents the price of the same REIT security at time *t* less the look-back period *k*.

3.4.2 Absolute momentum

The first part of the DM market timing rule is determining whether the asset currently being held exhibits positive or negative absolute momentum. Absolute momentum is calculated using the value obtained from equation 14 and subtracting the return achieved by the risk-free asset (T-bills) over the formation period of 12 months. The formula is as follows:

$$Absolute\ Momentum\ (AM)_i = R_{i,t=k} - Rf_{r,t=k} \tag{15}$$

This calculation is performed monthly so that it is consistent with the look-back period as well as the monthly return data employed in this study. The result of this calculation indicates the following:

$$AM_i > 0 = Positive\ absolute\ momentum \tag{16}$$

$$AM_i < 0 = Negative\ absolute\ momentum \tag{17}$$

Positive absolute momentum would indicate that the investor should hold or invest in the relevant primary buy-and-hold index. Conversely, negative absolute momentum would indicate the investor to hold or invest in the portfolio of domestic bonds.

[11] In the context of this study, long-term strategies refers to the average length of buying and holding underlying real estate properties owned and managed by REITs.

3.4.3 Relative momentum

The use of relative momentum as a second metric in this strategy allows an investor to rotate to an alternative index a. This rotation provides the investor with greater downside protection from losses resulting from holding a portfolio of bonds during market crises (Antonacci, 2014). The formula to calculate relative momentum is as follows:

$$R_{i,t=k} = \frac{P_{i,t=0} - P_{i,t-k}}{P_{i,t-k}} \tag{18}$$

In line with the approaches of Antonacci (2014) and Tonnessen (2018), Equation 15 is calculated in the instance where positive absolute momentum (Equation 16) exists. The result of equation 18 indicates the following:

$$R_{i,t=k} > 0 = Positive\ relative\ momentum \tag{19}$$

$$R_{i,t=k} < 0 = Negative\ relative\ momentum \tag{20}$$

Positive absolute (Equation 16) and positive relative momentum (Equation 19) signals a buy/hold signal, whereas positive absolute (Equation 16) and negative relative momentum (Equation 20) signals a sell signal.

3.5 Implementation of market timing rules

It is noteworthy that the purpose of this study is twofold, i.e. (i) investigating the effectiveness of the market timing strategies in REIT indices, and (ii) testing whether their effectiveness, if any, persists throughout the various market crises. As such, the market timing rules are first calculated, and their results compared, for the entire sample period. Thereafter, the same rules are applied to the indices during all three crisis periods and non-crisis periods.

3.6 Chapter summary

This chapter outlined and discussed the research methodology followed in this study including the quantitative research design, data transformations, and the methodology for implementing all four market timing rules. Chapter 4 provides a detailed description of the data employed in this study. This is done to understand the variables that comprise the market timing rules described in this chapter.

Chapter 4: Data and sample selection

The REIT and other data collected to implement the market timing strategies presented in the preceding chapter are described in this chapter.

4.1 Frequency of data

Market timing strategies have been applied to returns data for many different time horizons, as seen in Chapter 2 of this study. A monthly return interval is used for this analysis, where the returns represent the change in price on the last day of the month from the price on the last day of the previous month. This interval is consistent with Glabadanidis (2014) who motivates that monthly return observations provide better forecasting accuracy than daily return observations when analysing market timing in REITs. This is because REITs' securities are thinly traded in some markets. Monthly data thus acts as a filter for liquidity (Beau, 2019). The use of monthly returns data is further motivated by Berry, Gallinger and Henderson (1990) who argue that the use of daily data provides results that only offer short term insight and therefore cannot be repeated in future analysis. Monthly intervals are also used by most of the international market timing studies reviewed in Chapter 2, thus allowing for comparability with the existing literature.

4.2 Sample period

Determining an appropriate period to establish accurate and repeatable results is central to the purpose of conducting financial research. The sample period of this study ranges from 2 January 2001 to 31 December 2020. Conducting analysis over longer periods is likely to yield more reliable results. A period of 20 years is also selected since REITs have become more actively traded in more recent years in some markets chosen in this study than others. This is outlined in Chapter 1 of this study. A comparison can thus be made between the excess returns, if any, that can be derived from using market timing strategies and opting for a buy-and-hold strategy. This period also offers insight into the effectiveness of the selected market timing strategies during the (i) GFC; (ii) ESDC; and the (iii) Covid-19 pandemic.

The period of the GFC is defined as 16 September 2007 to 31 March 2009 (Abuzayed, Al-Fayoumi & Bouri, 2020). This includes the collapsing of Lehman Brothers and the subsequent contraction in global markets. Figure 3 provides a high-level timeline of the GFC depicting the change in economic growth across global markets resulting from the crisis. A unanimous contraction in market activity is signalled by lower economic growth as measured by GDP (Kose, Sugawara & Terrones, 2020). The graph indicates a unanimous timeline in the trend of economic growth over the period of the crisis across global markets.

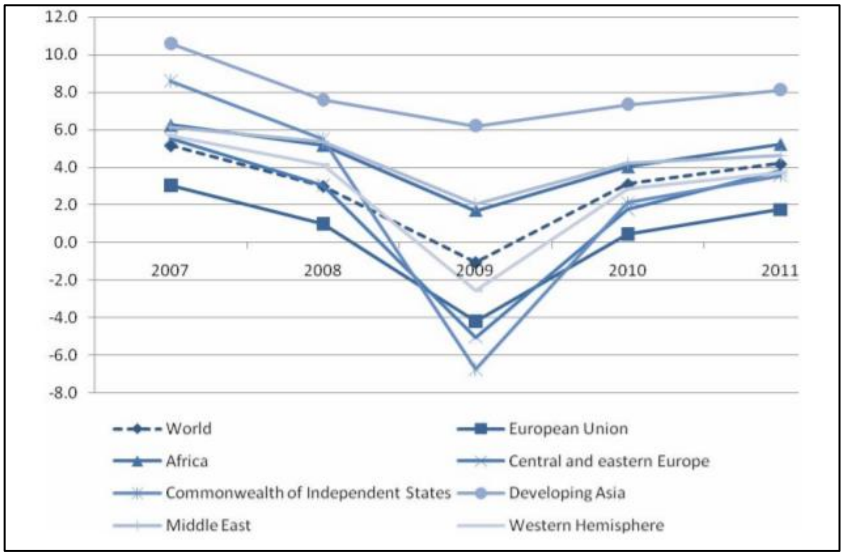

Figure 3:Change in economic growth per world region (Source: IMF World Economic Outlook Database, (2009)

The ESDC was characterised by the combination of collapsing European financial institutions, excessive public debt, and a significant rise in the long-term bond yield spreads of government securities (Kenton, 2020). Figure 4 below indicates that the ESDC peaked between 2010 and 2012 through depicting the peak and subsequent decline in bond yields for many countries forming part of the European Union. Abuzayed, Al-Fayoumi and Bouri (2020), discussed in section 2.2.2, define the ESDC according to the timeline of Alexakis et al. (2016), where the start of the crisis is defined as the 23 April 2010 when Greece’s sovereign debt insolvency became the debt crises of Europe and ended on 06 September 2012. For the purpose of this study, this range is used to define the period of the ESDC.

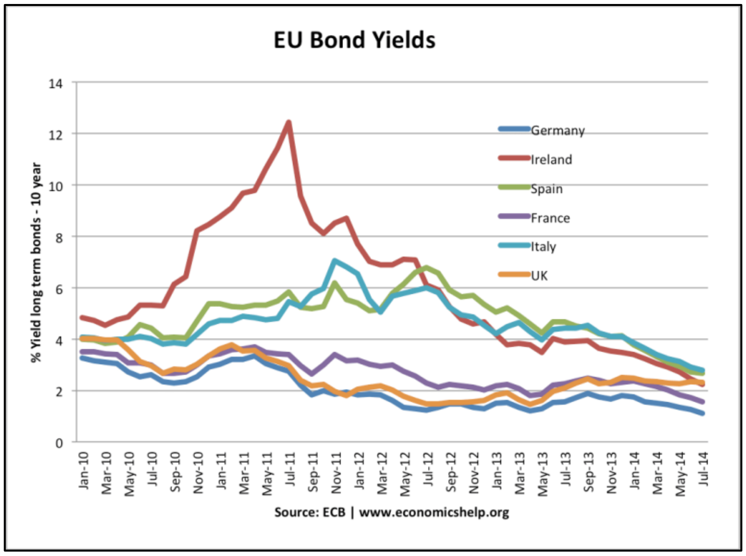

Figure 4:European Union bond yields throughout the ESDC (Source: Economics Help, 2016)

The Covid-19 pandemic is characterised by waves as a form of tracking the number of Covid-19 infections (Salyer et al. 2021). In the context of this pandemic, the authors define a wave as an increasing number of Covid-19 cases, with an identifiable peak, followed by a clear decreasing number of Covid-19 cases. Many countries included in the sample experienced a second wave of COVID-19, and some are still experiencing the second wave. The first wave of COVID-19 peaked at different times for the countries in the sample. Of the countries selected for the sample, SA experienced its peak the latest. This can be seen in Figure 5 below which depicts the 7-day moving average of daily new Covid-19 infections per global region. The graph depicts data from March 2020 to April 2021. To remain consistent with the analysis of the previous crises and in-line with using monthly data, the analysis is conducted until the end of the calendar month following the peak of the first wave of COVID-19 in SA.

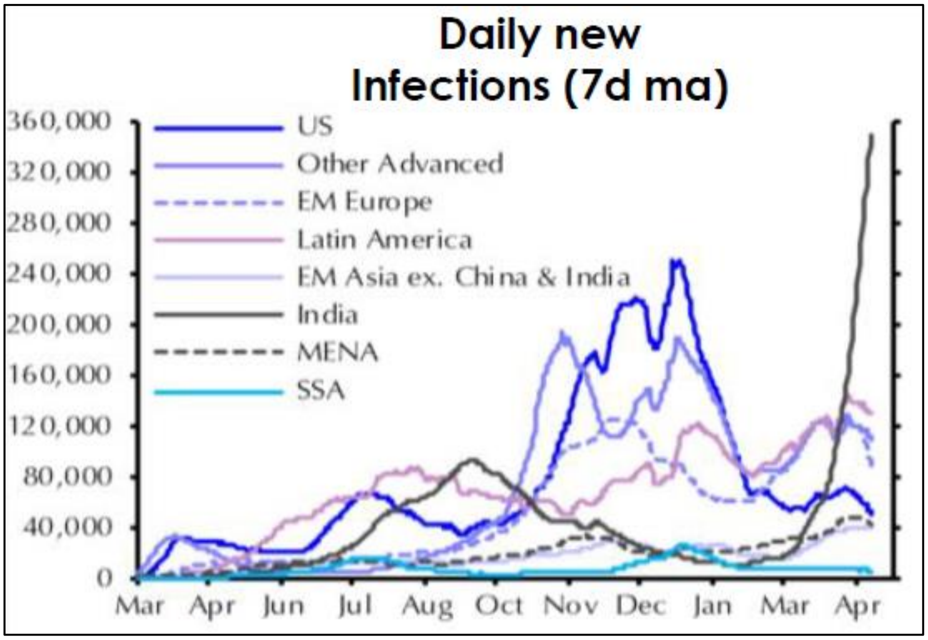

Figure 5:Covid-19 daily new infections (Source: Old Mutual, 2021)

4.3 REITs sample selection

The analysis conducted in this study employs market data from six of the largest REITs markets globally. As mentioned in Section 1.2, these markets, by market capitalisation, are the US (48.32%), Japan (10.43%), UK (4.24%), Australia (2.69%), Brazil (0.45%), and SA (0.30%). Consistent with the approach used by Han et al. (2013) and Marshall et al. (2013), the REITs used in this study are analysed from a portfolio perspective rather than individually. That is, REIT indices are analysed rather than individual REITs'securities[12]. In the context of this study, data of the REIT index for each market were obtained from Bloomberg[13]. Section 4.8 highlights the constraints applied to this data to mitigate any biases.

The model for REITs was established in the US in 1960 and has since become the pioneering model adopted in 40 markets globally (Brounen & de Koning, 2012; NAREIT, 2021). Typically the Dow Jones Composite REIT Total Return Index is used as a proxy for the US REIT market (Basse, Friedrich & Bea, 2009). However, the index consists of equity and non-equity REITs[14]. This study focuses on equity REITs only, since investors typically trade this sub-set of REITs'

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[12] The sample is therefore not subjected to survivorship bias, since indices adjust for newly listed and delisted stocks.
[13] As far as possible, comparable indices have been used in this study.
[14] According to NAREIT (2021), the four REIT types are: equity REITs, mortgage REITs, public non-listed REITs, and private REITs exempt from SEC registration.

securities. Therefore, the MSCI US REIT Index is selected for this study since it only comprises of US equity REITs. The indices subsequently discussed are also based on equity REITs only.

The Japanese REIT structure was adopted in 2001 and has a compelling investment presence amongst local and international investors (Newell & Peng, 2012). The REIT structure were introduced with the amendment to the Act on Investment Trusts and Investment Corporations (Investment Trust Act) in November 2000. Since the establishment of this asset class in Japan, the Japanese economy has seen rapid growth. As mentioned in Section 1.2 of this study, the Japanese market is heavily focused on property development. The MSCI Japan IMI REITs Index is selected as the representative index of the Japanese REIT market.

The REIT structure was adopted in 2007 in the UK and have exhibited noteworthy growth. UK REITs were classified as listed property prior to the formal adoption of the REIT structure in 2007 (Park, 2016). Unlike US REITs and J-REITs, UK REITs tend to hold diversified portfolios of real estate rather than managing real estate that have specific purposes. The focus for prospective and existing UK REITs, according to S&P Global Market Intelligence, has thus been to focus their business models on specialising in this sector. The NAREIT UK Index is selected as the representative index of the UK REIT market in order to maintain comparability with the indices used for the other markets in this study.

A-REITs were established on the ASX in 2008. Prior to their introduction on the Australian main board, A-REITs operated under a listed property structure (PLTs) that were akin to investing directly in physical real estate. The MSCI Australia Real Estate Index is selected as the representative index of the Australian REIT market in order to maintain comparability with the indices used for the other markets in this study. The data extracted includes securities of A-REITs that operated under the previous PLT structure. A-REITs that have been listed subsequent to the introduction of REITs in Australia have also been included in this sample.

The Brazilian REITs market was established in 1993 and has experienced significant growth since changes were made to their legal structure in 2008 (Yokoyama et al. 2017). The B3 Real Estate Investment Fund Index (IFIX) is selected as the representative index of the Brazilian REIT market in this study. The index was first released on September 3, 2012.

Similar to A-REITS, SA REITs also operated under separate listed property structures, that were akin to direct property investing, prior to the introduction of REITs on the main board of the local exchange in 2013. REITs that have been listed subsequent to the introduction of this sub-sector have also been included in the sample. For the purpose of this study, the FTSE/JSE SA REIT Index is selected as the representative index of the SA REIT market. The data obtained from Bloomberg includes securities of SA REITs that operated under these separate listed property structures.

Applying the four market timing rules to the indices described provides comparative insights of the effectiveness of these rules across varying REIT markets. However, it is also of value to construct a portfolio that is aligned to the needs of an investor seeking to invest in the global REIT market. To this end, a seventh hypothetical portfolio has been constructed by weighting the indices in according the size of the REIT markets outline in Section 1.2 of this study. The weights are adjusted proportionally to achieve a total allocation of 100%.

4.4 Treasury bills

Domestic T-bills, or their equivalent, with a duration of three months are selected as the risk-free proxy in all the markets selected. As explained in the previous chapter, under the first three market timing rules, investors rotate to a portfolio of T-Bills instead of using the T-bills to determine when to rotate between risky assets and safer assets. Under the DM market timing rule, the T-bill returns determine whether an investor should rotate the current investment in risky assets to a portfolio of government bonds or whether the investor should rotate the current investment in risky assets to a portfolio of global equities that are foreign to the domestic market in each country being reviewed. The T-bill proxies per country are presented in Appendix A.

4.5 Government bonds

The use of a portfolio of high-grade bonds is central to implementing the DM market timing rule of Antonacci (2014). In his study, Antonacci (2014) uses an absolute momentum method to determine whether an investor should invest in the S&P 500 index (in the event the S&P 500 index exhibits positive absolute momentum) or in the alternative safe haven portfolio of bonds (in the event the S&P 500 exhibits negative absolute momentum). Tonnessen (2018) replaces this portfolio of US government bonds with a Norwegian equivalent, since the study is only replicating an already tested rule. Therefore, a portfolio of high-grade bonds are established for every market in order to implement this rule since the DM market timing rule is also replicated in this study.

The bond indices attempt to match the US bond index used in this study as closely as possible, in order to achieve comparability. The bond proxies per country are presented in Appendix A.

4.6 Alternative indices

Implementing the DM market timing rule is based on both absolute and relative momentum. In order to determine which portfolio to buy or hold, Antonacci (2014) introduces a second index consisting of non-US equity securities. The equivalent of these indices are the stock indices representing the general stock market in the respective markets, since they prove to be the most liquid choices amongst investors. The alternative index proxies are presented in Appendix A.

4.7 Buy-and-hold sample selection

As established earlier in this study, the primary aim of the analysis is to determine whether or not investors can apply market timing strategies to REITs' indices in an attempt to outperform a corresponding buy-and-hold strategy. The literature reviewed in Chapter 2 provide numerous proxies for the buy-and-hold strategy. Ilomäki, Laurila and McAleer (2018) opted to invest in US T-bills as a passive portfolio for the buy-and-hold strategy in their implementation of the MA rule. In contrast, Zakamulin (2014) used passive benchmarks such as US stock- and government bond indices. Consistent with the approach of Zakamulin (2014), the buy-and-hold alternative to market timing REIT indices is holding the REIT indices.

4.8 Potential adjustments and biases

4.8.1 Time period bias

Empirical results are subject to time period bias when they are only observable within a chosen time period. This bias is indirectly acknowledged by Qin, Pan and Bai (2020) and De Chassart and Dumont (2002), amongst others in Chapter 2 of this study, who seek the most appropriate time periods to maximise excess returns derived from their market timing strategies. As observed from the review of prior research in Chapter 2, a shorter time period may provide results that cannot be achieved in future analysis (Berry, Gallinger & Henderson, 1990). Similarly, longer time periods may provide results that are statistically significant but are not entirely relevant as a result of material changes in the data. For example, REITs operated under different listed property structures in SA and Australia before these companies listed as REITs officially. The data of these companies under the old structures may thus appear irrelevant when drawing comparable results to REITs that have been listed for longer in the other markets under review.

This bias is mitigated because of the sample period of this study that ranges from 2 January 2001 to 31 December 2020. The transformation of listed property structures to REIT structures occurs within this period. Further, the period also covers significant changes to the structure of the market as defined by the effects of the GFC, ESDC, and the Covid-19 pandemic. Any data employed before the start date or after the end date of this period is thus irrelevant to the quantitative analysis.

4.8.2 Data snooping

Data snooping refers to an attempt to misuse the data to infer a predetermined statistically significant outcome (DeFusco, 2004). This attempt may distort a result that may only be attributable to chance or as a result of replicating an already successful analysis with the same inputs and parameters. In an attempt to mitigate this bias, multiple statistical metrics are calculated to compare the success of market timing strategies implemented in this study with the market timing strategies in previous literature.

4.8.3 Dividends

Koski and Scruggs (1998) explain that the price of equity securities falls when they lose their right to the next dividend payout (i.e. ex-dividend date). This is an important factor to consider for this study, as REITs are legally required to distribute a percentage of their earnings as dividends to investors more than once a year. Excluding dividends may result in false outliers (Toerien et al., 2014). In markets where REITs' securities are relatively new, unexpected events have the tendency to cause more erratic behaviour in the prices of these securities. However, to maintain sufficient data points for analysis in these markets, ex-dividend dates will be included. Rather, outliers will be assessed on a case-by-case basis to determine whether they are a result of the ordinary course of REIT operations (i.e. a result of legally obligated dividend distributions), or whether they are a result of a one time event not caused by the crises under review.

4.8.4 Outliers

Errors in the sample data or once-off events may produce outliers which have the potential to distort the data set. The data set is subject to a two-tailed winsorisation process, which opts not to remove any outliers but rather to replace them with the values of the 1st and 99th percentiles respectively. It is more appropriate to replace the values of these outliers since REITs are more thinly traded in some markets than others, and are thus subject to large movements in returns. Therefore, these outliers will be assessed on a case-by-case basis to determine whether they are spurious or whether they are as a result of a prevailing market crisis.

4.9 Chapter summary

This chapter described the data used to implement the market timing rules described in Chapter 3. Monthly data for the January 2001 to December 2020 is used. This sample period includes several market crises to enable the effectiveness of market timing to be evaluated during such periods. The latter part of the chapter described the REIT indices for which the returns data was obtained as well as other asset classes that are used in the implementation of the market timing rules. Chapter 5 presents and discusses the findings of the analysis.

Chapter 5

This chapter presents the results of the market timing rules described and applied in Chapters 3 and 4 of this study. The first section of this chapter presents the descriptive statistics of the data sample. The tables provide the detailed descriptive statistics output of the results in general and during the crises, respectively. The tests of normality discussed in subsection 3.2.2 are also examined in conjunction with the results of the market timing rules to discuss the reasons behind any non-normality in the returns data that may exist. The second section of this chapter provides a discussion of the results of the market timing rules within and across the selected markets over the sample period. The subsequent section discusses the effectiveness of the market timing rules over the three crises periods. Lastly, a summary of the results is provided.

5.1 Descriptive statistics

The analysis is carried out on all six REIT indices as well as the seventh hypothetical portfolio of REIT indices. As discussed in preceding chapters, there are four market timing rules that are applied to the selected data. As such, the tables and their subsequent discussions present the descriptive statistics for every market timing rule selected for this study.

5.1.1 Descriptive statistics of the MA market timing rule

The descriptive statistics of the MA results are shown in tables 1-7 below:

Table 1:Descriptive statistics of the MA market timing rule using US REIT data

	*Buy-and-hold**	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0075	0.0261	0.0235	0.0211	0.0200	0.0188	0.0149
Standard Error	0.0041	0.0021	0.0022	0.0023	0.0023	0.0023	0.0023
Median	0.0150	0.0150	0.0116	0.0100	0.0069	0.0059	0.0040
Standard Deviation	0.0641	0.0332	0.0343	0.0349	0.0357	0.0363	0.0364
Sample Variance	0.0041	0.0011	0.0012	0.0012	0.0013	0.0013	0.0013
Kurtosis	9.1700	13.4801	12.4181	11.3248	10.5130	9.9856	2.5955
Skewness	-1.6389	2.6808	2.5275	2.0977	1.9678	1.8913	-0.0928
Range	0.6565	0.2736	0.3118	0.3291	0.3349	0.3349	0.2951
Minimum	-0.3828	0.0000	-0.0382	-0.0555	-0.0612	-0.0612	-0.1604
Maximum	0.2736	0.2736	0.2736	0.2736	0.2736	0.2736	0.1347
Sum	1.8028	6.2729	5.6510	5.0656	4.8119	4.5079	3.5662
Count	240	240	240	240	240	240.0	240.00
Confidence Level(95.0%)	0.0081	0.0042	0.0044	0.0044	0.0045	0.0046	0.0046

**Buy-and-hold represents the statistics observed has an investor chosen to buy-and-hold the REIT index instead of using the market timing rule*

Table 2:Descriptive statistics of the MA market timing rule using J-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0059	0.0226	0.0207	0.0185	0.0186	0.0166	0.0132
Standard Error	0.0039	0.0023	0.0024	0.0023	0.0023	0.0026	0.0029
Median	0.0097	0.0097	0.0062	0.0005	0.0005	0.0005	0.0005
Standard Deviation	0.0585	0.0345	0.0357	0.0350	0.0351	0.0390	0.0435
Sample Variance	0.0034	0.0012	0.0013	0.0012	0.0012	0.0015	0.0019
Kurtosis	5.4213	14.9260	13.3195	15.2091	15.0271	15.4835	11.3006
Skewness	-0.6199	3.1576	2.9232	3.1772	3.1393	1.3938	0.5934
Range	0.5011	0.2591	0.2866	0.2866	0.2896	0.4787	0.4787
Minimum	-0.2423	-0.0003	-0.0277	-0.0277	-0.0308	-0.2199	-0.2199
Maximum	0.2589	0.2589	0.2589	0.2589	0.2589	0.2589	0.2589
Sum	1.3589	5.1825	4.7453	4.2315	4.2592	3.8123	3.0122
Count	229	229	229	229	229	229	229
Confidence Level(95.0%)	0.0076	0.0045	0.0046	0.0046	0.0046	0.0051	0.0057

Table 3:Descriptive statistics of the MA market timing rule using UK REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0004	0.0215	0.0190	0.0172	0.0162	0.0152	0.0105
Standard Error	0.0040	0.0020	0.0021	0.0021	0.0021	0.0022	0.0021
Median	0.0042	0.0045	0.0006	0.0005	0.0005	0.0005	0.0004
Standard Deviation	0.0621	0.0308	0.0324	0.0326	0.0333	0.0340	0.0323
Sample Variance	0.0039	0.0010	0.0011	0.0011	0.0011	0.0012	0.0010
Kurtosis	6.4951	8.9997	7.6890	7.9464	7.6447	7.0751	3.2098
Skewness	-1.3644	2.3231	2.0631	2.1074	1.9258	1.8281	0.7881
Range	0.5758	0.2222	0.2730	0.2730	0.2879	0.2879	0.2719
Minimum	-0.3536	0.0000	-0.0508	-0.0508	-0.0657	-0.0657	-0.0987
Maximum	0.2222	0.2222	0.2222	0.2222	0.2222	0.2222	0.1731
Sum	-0.1064	5.1688	4.5662	4.1392	3.8830	3.6396	2.5294
Count	240	240	240	240	240	240	240
Confidence Level(95.0%)	0.0079	0.0039	0.0041	0.0041	0.0042	0.0043	0.0041

Table 4:Descriptive statistics of the MA market timing rule using A-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0004	0.0175	0.0156	0.0133	0.0127	0.0123	0.0091
Standard Error	0.0035	0.0015	0.0015	0.0016	0.0016	0.0016	0.0017
Median	0.0057	0.0058	0.0047	0.0041	0.0040	0.0039	0.0025
Standard Deviation	0.0544	0.0236	0.0237	0.0255	0.0251	0.0252	0.0269
Sample Variance	0.0030	0.0006	0.0006	0.0006	0.0006	0.0006	0.0007
Kurtosis	20.4310	5.3937	3.9563	4.2120	4.5841	4.5636	3.9202
Skewness	-3.0805	2.0461	1.6708	1.0407	1.0400	1.0142	0.7008
Range	0.5674	0.1321	0.1598	0.2268	0.2268	0.2268	0.2268
Minimum	-0.4353	0.0000	-0.0277	-0.0947	-0.0947	-0.0947	-0.0947
Maximum	0.1321	0.1321	0.1321	0.1321	0.1321	0.1321	0.1321
Sum	0.0935	4.1708	3.7326	3.1712	3.0244	2.9328	2.1639
Count	239	239	239	239	239	239	239
Confidence Level(95.0%)	0.0069	0.0030	0.0030	0.0032	0.0032	0.0032	0.0034

Table 5:Descriptive statistics of the MA market timing rule using Brazilian REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0089	0.0194	0.0174	0.0162	0.0157	0.0153	0.0147
Standard Error	0.0031	0.0016	0.0018	0.0018	0.0019	0.0019	0.0020
Median	0.0136	0.0136	0.0124	0.0118	0.0114	0.0113	0.0107
Standard Deviation	0.0331	0.0173	0.0191	0.0198	0.0202	0.0209	0.0214
Sample Variance	0.0011	0.0003	0.0004	0.0004	0.0004	0.0004	0.0005
Kurtosis	7.4256	5.1369	4.1195	3.6870	3.4321	3.1242	2.9422
Skewness	-1.4862	1.9556	1.2749	1.1716	1.1049	0.9071	0.7952
Range	0.2736	0.1008	0.1394	0.1394	0.1394	0.1394	0.1414
Minimum	-0.1725	0.0002	-0.0383	-0.0383	-0.0383	-0.0383	-0.0404
Maximum	0.1010	0.1010	0.1010	0.1010	0.1010	0.1010	0.1010
Sum	1.0539	2.2884	2.0512	1.9116	1.8563	1.7997	1.7391
Count	118	118	118	118	118	118	118
Confidence Level(95.0%)	0.0060	0.0032	0.0035	0.0036	0.0037	0.0038	0.0039

Table 6:Descriptive statistics of the MA market timing rule using SA REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0032	0.0223	0.0202	0.0187	0.0177	0.0160	0.0115
Standard Error	0.0091	0.0039	0.0041	0.0042	0.0041	0.0035	0.0034
Median	0.0047	0.0047	0.0032	0.0031	0.0031	0.0031	0.0031
Standard Deviation	0.0795	0.0345	0.0358	0.0365	0.0362	0.0308	0.0298
Sample Variance	0.0063	0.0012	0.0013	0.0013	0.0013	0.0009	0.0009
Kurtosis	20.4171	7.3040	6.7304	6.4814	7.0188	7.4256	4.7250
Skewness	-3.1978	2.6109	2.4013	2.3034	2.4002	2.4658	1.2594
Range	0.6754	0.1721	0.2193	0.2193	0.2193	0.1971	0.1920
Minimum	-0.5027	0.0006	-0.0466	-0.0466	-0.0466	-0.0439	-0.0586
Maximum	0.1727	0.1727	0.1727	0.1727	0.1727	0.1532	0.1335
Sum	-0.2486	1.7175	1.5550	1.4421	1.3606	1.2338	0.8882
Count	77	77	77	77	77	77	77
Confidence Level(95.0%)	0.0180	0.0078	0.0081	0.0083	0.0082	0.0070	0.0068

Table 7:Descriptive statistics of the MA market timing rule using the Hypothetical Portfolio data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0067	0.0231	0.0206	0.0192	0.0179	0.0167	0.0138
Standard Error	0.0037	0.0019	0.0019	0.0020	0.0021	0.0020	0.0021
Median	0.0130	0.0130	0.0104	0.0097	0.0061	0.0053	0.0038
Standard Deviation	0.0569	0.0290	0.0294	0.0309	0.0321	0.0317	0.0322
Sample Variance	0.0032	0.0008	0.0009	0.0010	0.0010	0.0010	0.0010
Kurtosis	9.8242	10.5220	10.3931	8.7094	7.7721	8.2531	2.4704
Skewness	-1.8162	2.4703	2.3655	1.9310	1.6976	1.7108	0.4099
Range	0.5725	0.2208	0.2568	0.2798	0.2842	0.2842	0.2613
Minimum	-0.3517	0.0001	-0.0360	-0.0590	-0.0633	-0.0633	-0.1095
Maximum	0.2209	0.2209	0.2209	0.2209	0.2209	0.2209	0.1518
Sum	1.5992	5.5391	4.9441	4.6010	4.2852	4.0184	3.3088
Count	240	240	240	240	240	240	240
Confidence Level(95.0%)	0.0072	0.0037	0.0037	0.0039	0.0041	0.0040	0.0041

In general, the average return achieved under the MA market timing rule per market is consistently greater than average return achieved when opting to buy-and-hold the respective REIT index, which is the alternative to implementing the market timing rule. Specifically, this market timing rule yields the highest average return in the US at the 2 month MA period (2.6%) while the lowest average return is found in Australia at the 12 month MA period (0.91%). The results also indicate that these returns diminish as the MA period increases above six months. This indicates that the MA market timing rule may provide some predictive ability when considering shorter MA periods as opposed to longer MA periods. This result is also observed by Glabadanidis (2014). As mentioned in chapter 2, Black (1986) and Liu et al. (2019) find that although market noise provides short term inefficiencies in the market, the added liquidity provides opportunities to time the market. This buying and selling activity will thus bring the market back into equilibrium.

The standard deviation of the MA strategy returns increases marginally over all observed MA periods for every market examined, indicating a greater dispersion of MA returns around their respective means as a greater MA period is used. This is consistent with the increase in the range of MA returns over all periods. However, the respective standard deviations are significantly lower than the standard deviations observed had an investor chosen to follow the buy-and-hold strategy. This lower dispersion is also observed when analysing the range of returns which are tighter than the range observed for the buy-and-hold strategy. The range of returns under the MA rule generally have a higher minimum return compared to the minimum return of the buy-and-hold strategy. The results also indicate that the maximum returns are mostly in line, if not identical, to the maximum return achieved by the buy-and-hold strategy. Specifically, this market timing rule yields the highest returns in the US (27.4%) and yields the lowest return for the hypothetical portfolio (-6.3%) in any one month. Therefore, while the upside potential is limited to the same maximum return of the buy-and-hold strategy, it avoids the potential losses that could arise during periods when the index performs poorly. The correlation tables are included in Appendix B:Correlations.

The returns of the buy-and-hold strategy are negatively skewed in every market. This indicates that the majority of returns achieved under this strategy are below the mean return for the REIT index in every market. Consistent with the diminishing returns, the MA returns become more positively skewed until the point the six-month MA is used; thereafter the positive skewness starts to diminish. This indicates that the majority of returns achieved under this strategy are above the MA mean return for the MA rules based on the shorter MA horizons.

Observing the kurtosis also provides insight into the normality of the data set. Generally, a coefficient of three deems the data set to be normal (Brooks, 2008). The MA results indicate kurtosis coefficients greater than 3 for all six REIT indices, with notably large kurtosis coefficients around 20 observed in the Australian and South African REIT index lognormal returns. As mentioned in section 3.2.2 of this study, the REIT markets being analysed are at different maturities. The large kurtosis coefficients thus reinforces that the actual returns contain many outliers in the less mature markets, such as Australia and SA, as opposed to more mature markets such as the US. Interestingly, the kurtosis coefficients generated under the varying lengths of MAs are consistently greater than the kurtosis coefficients of the lognormal returns of the selected REIT indices for the US, Japan, and the UK[15].The coefficients of Australia, Brazil, and SA are consistently below the coefficient of the selected REIT indices' lognormal returns, but still above the acceptable level of 3. The JB and SW tests corroborates the kurtosis and skewness statistics.

The seventh hypothetical portfolio, which represents a hypothetical portfolio aimed at global investors, achieves the same results as the more mature markets. This is because the mature markets are larger in size and thus carry a greater weighting in the formation of this portfolio. Unlike the standalone indices, the standard deviation of this portfolio only has marginal fluctuations. This may allude to the fact that the inclusion of multiple REIT indices in one portfolio provides some diversification and subsequent lower risk. The MA skewness and kurtosis coefficients, although marginally higher, are also in closer to proximity to the skewness and kurtosis coefficients of the individual REIT indices' returns. The close proximity of the MA statistics to the actual statistics may be indicative that an MA timing rule can be applied more reliably to a diversified portfolio as opposed to a single index. However, this will be discussed in further detail later in this chapter. The JB and SW tests corroborate the kurtosis and skewness statistics.

The measure of success for this rule is observed when the MA returns consistently outperform the returns of the buy-and-hold strategy as seen in the results of this study suggesting that the MA rule, especially at short horizons, can be used to time REIT indices. The results discussed above are consistent with many of the findings discussed in section 2.1.1 of this study. For example, Gartley (1935) confirms that the use of the MA as a market timer reduces the overall risk to the investor by providing a clear trend of stock price movements and removing immaterial price fluctuations. This principle is observed when observing that the deviation in returns under the MA

[15] These REIT markets are more mature because of their longer track record in relation to the other markets.

timing rule is consistently less than the deviation in returns of the buy-and-hold alternative. The results for market timing REITs are similar to the results of the studies investigating the market timing ability of stocks in chapter 2. The lower volatility is also observed by Ilomäki, Laurila and McAleer (2018) and De Chassart and Dumont (2002), who find that this lower volatility translates into an increased timing ability. However, De Chassart and Dumont (2002) and Faber (2007) acknowledge that implementing this rule successfully is substantially dependent on identifying the optimal market phase to implement. The success of this rule during varying market crises is discussed later in this chapter.

5.1.2 Descriptive statistics of the TSM market timing rule

The statistics of the TSM results are shown in tables 8-14 below:

Table 8:Descriptive statistics of the TSM market timing rule using US REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0075	0.0154	0.0104	0.0109	0.0088	0.0086	0.0073
Standard Error	0.0042	0.0023	0.0024	0.0024	0.0025	0.0025	0.0028
Median	0.0157	0.0035	0.0020	0.0017	0.0015	0.0015	0.0057
Standard Deviation	0.0642	0.0358	0.0367	0.0370	0.0391	0.0392	0.0440
Sample Variance	0.0041	0.0013	0.0014	0.0014	0.0015	0.0015	0.0019
Kurtosis	9.1218	11.2486	2.6693	2.3282	1.9178	1.9016	4.8069
Skewness	-1.6362	1.7988	-0.2978	-0.2401	-0.3117	-0.3775	-1.1299
Range	0.6565	0.3636	0.2917	0.2917	0.2917	0.2951	0.3782
Minimum	-0.3828	-0.0900	-0.1604	-0.1604	-0.1604	-0.1604	-0.2436
Maximum	0.2736	0.2736	0.1312	0.1312	0.1312	0.1347	0.1347
Sum	1.7986	3.6780	2.4967	2.5987	2.0986	2.0520	1.7422
Count	239	239	239	239	239	239	239
Confidence Level(95.0%)	0.0082	0.0046	0.0047	0.0047	0.0050	0.0050	0.0056

Table 9:Descriptive statistics of the TSM market timing rule using J-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0066	0.0143	0.0122	0.0095	0.0090	0.0073	0.0064
Standard Error	0.0036	0.0024	0.0025	0.0026	0.0026	0.0029	0.0031
Median	0.0101	0.0005	0.0005	0.0005	0.0004	0.0004	0.0002
Standard Deviation	0.0537	0.0357	0.0365	0.0382	0.0390	0.0422	0.0451
Sample Variance	0.0029	0.0013	0.0013	0.0015	0.0015	0.0018	0.0020
Kurtosis	5.3518	9.6716	8.8521	7.5805	7.5628	9.7543	8.0563
Skewness	-0.9008	1.1319	0.6612	0.3162	0.5192	-0.3974	-0.4541
Range	0.4664	0.3906	0.3906	0.3906	0.3906	0.4572	0.4572
Minimum	-0.2423	-0.1665	-0.1665	-0.1665	-0.1665	-0.2330	-0.2330
Maximum	0.2241	0.2241	0.2241	0.2241	0.2241	0.2241	0.2241
Sum	1.4306	3.1112	2.6560	2.0644	1.9589	1.5992	1.3995
Count	218	218	218	218	218	218	218
Confidence Level(95.0%)	0.0072	0.0048	0.0049	0.0051	0.0052	0.0056	0.0060

Table 10:Descriptive statistics of the TSM market timing rule using UK REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0010	0.0112	0.0191	0.0173	0.0162	0.0039	0.0024
Standard Error	0.0037	0.0023	0.0021	0.0021	0.0022	0.0024	0.0023
Median	0.0042	0.0004	0.0006	0.0005	0.0005	0.0003	0.0002
Standard Deviation	0.0579	0.0361	0.0325	0.0326	0.0333	0.0368	0.0356
Sample Variance	0.0033	0.0013	0.0011	0.0011	0.0011	0.0014	0.0013
Kurtosis	3.7715	6.3459	7.6550	7.9080	7.6060	5.2889	1.6383
Skewness	-0.8083	1.4526	2.0567	2.1007	1.9191	-0.9756	-0.3669
Range	0.4769	0.3209	0.2730	0.2730	0.2879	0.3046	0.2085
Minimum	-0.2547	-0.0987	-0.0508	-0.0508	-0.0657	-0.2100	-0.1139
Maximum	0.2222	0.2222	0.2222	0.2222	0.2222	0.0946	0.0946
Sum	0.2473	2.6677	4.5662	4.1392	3.8830	0.9289	0.5835
Count	239	239	239	239	239	239	239
Confidence Level(95.0%)	0.0074	0.0046	0.0041	0.0042	0.0042	0.0047	0.0045

Table 11:Descriptive statistics of the TSM market timing rule using A-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0004	0.0077	0.0068	0.0053	0.0039	0.0049	0.0021
Standard Error	0.0035	0.0017	0.0018	0.0018	0.0018	0.0017	0.0027
Median	0.0057	0.0016	0.0006	0.0001	0.0000	0.0001	0.0001
Standard Deviation	0.0544	0.0269	0.0274	0.0280	0.0273	0.0263	0.0416
Sample Variance	0.0030	0.0007	0.0007	0.0008	0.0007	0.0007	0.0017
Kurtosis	20.4310	4.1400	3.9757	3.9192	2.8470	1.5454	51.3664
Skewness	-3.0805	0.6263	0.6922	0.5700	0.1992	-0.2211	-5.0068
Range	0.5674	0.2268	0.2268	0.2268	0.2191	0.1740	0.5640
Minimum	-0.4353	-0.0947	-0.0947	-0.0947	-0.0947	-0.0947	-0.4353
Maximum	0.1321	0.1321	0.1321	0.1321	0.1244	0.0793	0.1287
Sum	0.0935	1.8372	1.6149	1.2685	0.9208	1.1727	0.5039
Count	239	239	239	239	239	239	239
Confidence Level(95.0%)	0.0069	0.0034	0.0035	0.0036	0.0035	0.0034	0.0053

Table 12:Descriptive statistics of the TSM market timing rule using Brazilian REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0089	0.0148	0.0127	0.0105	0.0093	0.0083	0.0108
Standard Error	0.0031	0.0019	0.0020	0.0025	0.0026	0.0027	0.0008
Median	0.0136	0.0107	0.0109	0.0102	0.0098	0.0095	0.0097
Standard Deviation	0.0331	0.0210	0.0216	0.0270	0.0277	0.0295	0.0091
Sample Variance	0.0011	0.0004	0.0005	0.0007	0.0008	0.0009	0.0001
Kurtosis	7.4256	2.9239	2.7539	18.3489	15.9143	12.2629	-0.5142
Skewness	-1.4862	0.9724	0.2747	-2.4343	-2.2130	-2.0458	0.1417
Range	0.2736	0.1394	0.1552	0.2736	0.2736	0.2736	0.0432
Minimum	-0.1725	-0.0383	-0.0541	-0.1725	-0.1725	-0.1725	-0.0111
Maximum	0.1010	0.1010	0.1010	0.1010	0.1010	0.1010	0.0321
Sum	1.0539	1.7450	1.4929	1.2351	1.0970	0.9747	1.2777
Count	118	118	118	118	118	118	118
Confidence Level(95.0%)	0.0060	0.0038	0.0039	0.0049	0.0051	0.0054	0.0017

Table 13:Descriptive statistics of the TSM market timing rule using SA REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0032	0.0151	0.0106	0.0093	0.0089	0.0064	0.0053
Standard Error	0.0091	0.0026	0.0022	0.0021	0.0021	0.0033	0.0036
Median	0.0047	0.0031	0.0031	0.0031	0.0031	0.0031	0.0031
Standard Deviation	0.0795	0.0230	0.0189	0.0185	0.0181	0.0290	0.0318
Sample Variance	0.0063	0.0005	0.0004	0.0003	0.0003	0.0008	0.0010
Kurtosis	20.4171	8.7671	23.2860	26.3150	29.7149	3.0120	1.7378
Skewness	-3.1978	2.5586	4.1213	4.2974	4.6321	-0.2135	-0.1663
Range	0.6754	0.1420	0.1446	0.1521	0.1522	0.1799	0.1799
Minimum	-0.5027	-0.0085	-0.0111	-0.0186	-0.0187	-0.0806	-0.0806
Maximum	0.1727	0.1335	0.1335	0.1335	0.1335	0.0993	0.0993
Sum	-0.2486	1.1627	0.8142	0.7124	0.6852	0.4924	0.4106
Count	77	77	77	77	77	77	77
Confidence Level(95.0%)	0.0180	0.0052	0.0043	0.0042	0.0041	0.0066	0.0072

Table 14:Descriptive statistics of the TSM market timing rule using the Hypothetical Portfolio REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0068	0.0138	0.0111	0.0107	0.0088	0.0071	0.0069
Standard Error	0.0037	0.0021	0.0021	0.0021	0.0023	0.0025	0.0026
Median	0.0130	0.0030	0.0025	0.0024	0.0013	0.0013	0.0054
Standard Deviation	0.0570	0.0326	0.0324	0.0325	0.0349	0.0388	0.0402
Sample Variance	0.0032	0.0011	0.0011	0.0011	0.0012	0.0015	0.0016
Kurtosis	9.8190	8.3722	2.9549	2.3799	2.3091	8.6917	7.3746
Skewness	-1.8219	1.3682	0.2038	0.3178	0.0324	-1.2381	-1.2288
Range	0.5725	0.3303	0.2674	0.2613	0.2613	0.4023	0.4023
Minimum	-0.3517	-0.1095	-0.1155	-0.1095	-0.1095	-0.2504	-0.2504
Maximum	0.2209	0.2209	0.1518	0.1518	0.1518	0.1518	0.1518
Sum	1.6231	3.2909	2.6491	2.5514	2.1093	1.6882	1.6497
Count	239	239	239	239	239	239	239
Confidence Level(95.0%)	0.0073	0.0042	0.0041	0.0041	0.0044	0.0049	0.0051

In general, the average return achieved under the TSM market timing rule per market are consistently greater than the average return achieved opting to buy-and-hold the respective REIT index. Specifically, the TSM market timing rule yields the highest at the 3 month TSM period (1.91%) and lowest average at the 12 month TSM (0.2%) returns in the UK. Similar to the MA market timing rule, the average return starts reverting to the mean return of the buy-and-hold strategy after the 6-month TSM for all six markets as well as the seventh hypothetical portfolio. This reversion indicates that the predictive ability of the TSM rule starts to decline over longer lookback periods. The standard deviations for all TSM periods are significantly lower than the standard deviation of the respective buy-and-hold indices for all markets. This indicates that the strategy generally carries a lower overall risk than the buy-and-hold strategy. The lower risk is attributable to inclusion of the risk-free rate earned by the investor in the instance that the portfolio rotates from the REIT index (i.e. the risky asst) to the portfolio of T-Bills. Therefore, lower standard deviation is positively correlated with an increase in sell signals under this rule. The description of the returns and standard deviation is consistent with the findings of Qin, Pan and Bai (2020) who examined the ability of the TSM to outperform a buy-and-hold strategy on stocks contained in the Shanghai and Shenzhen 300 index. As with the MA rule, the range of returns under the TSM rule also has a higher minimum return compared to the minimum return of the buy-and-hold strategy. The maximum returns are for the most part also identical to the maximum return achieved by the buy-and-hold strategy, with a decline occurring after the 6-month TSM. Specifically, this market timing rule yields the highest return in the US (27.4%) and yields the lowest return in SA (-0.85%) in any one month. Therefore, while the upside potential is limited to the same maximum return of the buy-and-hold strategy, it avoids the potential losses that could arise during periods when the index performs poorly.

The correlation of the returns achieved under TSM market timing rule are presented in Appendix B:Correlations. The results also indicate that the TSM returns are positively skewed for shorter TSM periods but start exhibiting negative skewness for longer TSM periods. This is observed in the results of all six markets, indicating that the TSM market timing rule provides an investor with greater short term upside potential than following a buy-and-hold strategy. The kurtosis coefficients are generally greater than their counter buy-and-hold coefficients. The greater peaks are indicative of potential outliers which will be addressed later in this chapter. The JB and SW tests corroborates the kurtosis and skewness statistics.

The studies reviewed in section 2.1.2 indicate that the profitability of the TSM market timing rule is largely attributable to the market cycle in which it is applied. Of the reviewed literature for this rule, the results of the TSM rule in this study is mostly consistent with that of Qin, Pan and Bai

(2020). This study also determined the success of the market timing rules by observing the returns it yields under varying lengths of momentum. As highlighted by Qin, Pan and Bai (2020), and observed in this study, the TSM returns tend to decline over longer periods. The authors thus suggest that the rule would need to follow a rebalancing to ascertain the length of the TSM period that would yield the greatest return. Although not within the scope of this study, the cost of rebalancing may be a contributing factor to the diminishing returns observed. In turn, this may affect the forecasting ability of this rule. As suggested by Bird, Gao and Yeung (2017) the profitability of this rule may be further enhanced by combining it with a traditional cross-sectional momentum strategy.

5.1.3 Descriptive statistics of the MMAC market timing rule

Since only the optimal variation of this rule has been applied in this study, no comparative discussion exists across the variations. However, comparisons can be drawn across the statistics of the various markets. The statistics of the MMAC results are shown in tables 15-21 below:

Table 15:Descriptive statistics of the MMAC market timing rule using US REIT data

	Buy-and-hold	*MMAC return*
Mean	0.0075	0.0185
Standard Error	0.0041	0.0022
Median	0.0150	0.0142
Standard Deviation	0.0641	0.0345
Sample Variance	0.0041	0.0012
Kurtosis	9.1700	0.8685
Skewness	-1.6389	0.2753
Range	0.6565	0.2263
Minimum	-0.3828	-0.0861
Maximum	0.2736	0.1403
Sum	1.8028	4.4315
Count	240	240
Confidence Level(95.0%)	0.0081	0.0044

Table 16:Descriptive statistics of the MMAC market timing rule using J-REIT data

	Buy-and-hold	*MMAC return*
Mean	0.0059	0.0146
Standard Error	0.0039	0.0030
Median	0.0097	0.0056
Standard Deviation	0.0585	0.0446
Sample Variance	0.0034	0.0020
Kurtosis	5.4213	13.0990
Skewness	-0.6199	1.3988
Range	0.5011	0.4928
Minimum	-0.2423	-0.1974
Maximum	0.2589	0.2955
Sum	1.3589	3.3372
Count	229	229
Confidence Level(95.0%)	0.0076	0.0058

Table 17:Descriptive statistics of the MMAC market timing rule using UK REIT data

	Buy-and-hold	*MMAC return*
Mean	-0.0004	0.0138
Standard Error	0.0040	0.0022
Median	0.0042	0.0043
Standard Deviation	0.0621	0.0344
Sample Variance	0.0039	0.0012
Kurtosis	6.4951	3.1659
Skewness	-1.3644	0.8912
Range	0.5758	0.2831
Minimum	-0.3536	-0.0940
Maximum	0.2222	0.1890
Sum	-0.1064	3.3185
Count	240	240
Confidence Level(95.0%)	0.0079	0.0044

Table 18 Descriptive statistics of the MMAC market timing rule using A-REIT data

	Buy-and-hold	*MMAC return*
Mean	0.0027	0.0271
Standard Error	0.0042	0.0037
Median	0.0057	0.0234
Standard Deviation	0.0654	0.0568
Sample Variance	0.0043	0.0032
Kurtosis	31.8753	116.2378
Skewness	0.8401	9.0243
Range	1.0006	0.8504
Minimum	-0.4353	-0.0903
Maximum	0.5654	0.7601
Sum	0.6589	6.5146
Count	240	240
Confidence Level(95.0%)	0.0083	0.0072

Table 19:Descriptive statistics of the MMAC market timing rule using Brazilian REIT data

	Buy-and-hold	*MMAC return*
Mean	0.0088	0.0394
Standard Error	0.0030	0.0041
Median	0.0136	0.0253
Standard Deviation	0.0330	0.0453
Sample Variance	0.0011	0.0020
Kurtosis	7.4574	-0.1685
Skewness	-1.4787	0.8848
Range	0.2736	0.1896
Minimum	-0.1725	-0.0376
Maximum	0.1010	0.1520
Sum	1.0487	4.6870
Count	119	119
Confidence Level(95.0%)	0.0060	0.0082

Table 20: Descriptive statistics of the MMAC market timing rule using SA REIT data

	Buy-and-hold	*MMAC return*
Mean	-0.0029	0.0283
Standard Error	0.0090	0.0035
Median	0.0055	0.0371
Standard Deviation	0.0790	0.0305
Sample Variance	0.0062	0.0009
Kurtosis	20.7039	3.7739
Skewness	-3.2236	-0.0126
Range	0.6754	0.1997
Minimum	-0.5027	-0.0569
Maximum	0.1727	0.1428
Sum	-0.2292	2.2040
Count	78	78
Confidence Level(95.0%)	0.0178	0.0069

Table 21:Descriptive statistics of the MMAC market timing rule using the Hypothetical Portfolio REIT data

	Buy-and-hold	*MMAC return*
Mean	0.0067	0.0173
Standard Error	0.0037	0.0020
Median	0.0130	0.0139
Standard Deviation	0.0569	0.0317
Sample Variance	0.0032	0.0010
Kurtosis	9.8242	3.0161
Skewness	-1.8162	0.3699
Range	0.5725	0.2677
Minimum	-0.3517	-0.1037
Maximum	0.2209	0.1640
Sum	1.5992	4.1635
Count	240	240
Confidence Level(95.0%)	0.0072	0.0040

Similar to the previous two strategies, the average return achieved under the MMAC market timing rule per market is consistently greater than the average return achieved when not implementing this market timing rule. The average MMAC returns in the US (1.8%), Japan (1.5%), and the UK (1.4%) are lower than the average MMAC returns in Australia (2.7%), Brazil (3.9%), and SA (2.8%). The seventh hypothetical portfolio yields an average return of (1.7%). This may be indicative of this timing rule capturing higher returns more consistently in the latter markets than in the former.

Looking at the correlation matrix table below (Table 6), it is observed that there are general mild to moderate positive correlations between the returns of holding the REIT index and the MMAC returns within every market. However, negative correlation exists in the Brazilian market.

	Lognormal rtn
Lognormal rtn	1
US returns	0.5385
JPY returns	0.7706
UK returns	0.6104
Aus returns	0.2275
Brazil returns	-0.0592
SA returns	0.2641
Hyp portfolio returns	0.557

Figure 6:Correlation table of MMAC returns

With the exception of the Brazilian market, the standard deviation is also consistently lower for the MMAC rule. Again, this is attributable to the rotation between the REIT index and a portfolio of T-Bills. The lower standard deviation is also attributable to the use of indices instead of individual REITs, as found by Patari and Vilka (2014).

The results indicate that the MMAC returns are positively skewed in all markets, except in SA where there is a marginal negative skewness in the returns. Assessed together with the positive MMAC mean returns, it can be deduced that negative skewness across all markets exists, had the market timing rule not been implemented. The kurtosis coefficients provide mixed results, with some being extremely positive and some being marginally below 0. This reinforces that investors will achieve more extreme returns in some markets, such as Japan (29.5%) and Australia (76%), as opposed to the US (14.0%), UK (18.9%), Brazil (15.2%), and SA (14.3%) in any one month. However, these extreme returns may not be consistent. The JB and SW tests corroborates the kurtosis and skewness statistics.

The results of this rule are largely consistent with the findings of the studies reviewed in section 2.1.3 of this study. The returns, ignoring costs, are consistently greater than the returns of the buy-and-hold strategy. Patari and Vilka (2014) and Anghel (2013) assert that the profitability of the MMAC timing rule is largely dependent on the market cycle in which it is applied as well as the associated tax and transaction costs incurred to implement it. Patari and Vilka (2014) indicate that applying the market timing rule to indices or portfolios rather than individual stocks provides the investor with lower overall risk, especially where markets are defined by higher liquidity. This is directly applicable to REITs. The results indicate that markets where REITs are more thinly traded (i.e. Australia, Brazil, and SA), the more sporadic returns are accompanied by larger values of standard deviation. In markets where REITs are more actively traded (i.e. US, Japan, and UK), the returns still exceed the buy-and-hold strategy but at a lower standard deviation than the former markets' results.

5.1.4 Descriptive statistics of the DM market timing rule

The statistics of the DM results are shown in tables 22-28 below:.

Table 22: Descriptive statistics of the DM market timing rule using US REIT data

	Buy-and-hold	*DM rtn*
Mean	0.0075	0.1565
Standard Error	0.0043	0.0108
Median	0.0157	0.1205
Standard Deviation	0.0652	0.1634
Sample Variance	0.0043	0.0267
Kurtosis	8.8961	6.9837
Skewness	-1.6293	1.9618
Range	0.6565	1.1281
Minimum	-0.3828	-0.0234
Maximum	0.2736	1.1047
Sum	1.7077	35.8354
Count	229	229
Confidence Level(95.0%)	0.0085	0.0213

Table 23: Descriptive statistics of the DM market timing rule using J-REIT data

	Buy-and-hold	*DM rtn*
Mean	0.0066	0.1539
Standard Error	0.0036	0.0107
Median	0.0101	0.1277
Standard Deviation	0.0537	0.1586
Sample Variance	0.0029	0.0252
Kurtosis	5.3518	0.9752
Skewness	-0.9008	1.0735
Range	0.4664	0.7552
Minimum	-0.2423	-0.0156
Maximum	0.2241	0.7397
Sum	1.4306	33.5595
Count	218	218
Confidence Level(95.0%)	0.0072	0.0212

Table 24: Descriptive statistics of the DM market timing rule using UK REIT data

	Buy-and-hold	*DM rtn*
Mean	0.0016	0.1198
Standard Error	0.0039	0.0091
Median	0.0045	0.0589
Standard Deviation	0.0586	0.1375
Sample Variance	0.0034	0.0189
Kurtosis	3.7030	0.2551
Skewness	-0.8119	1.0054
Range	0.4769	0.6414
Minimum	-0.2547	-0.0763
Maximum	0.2222	0.5651
Sum	0.3647	27.4232
Count	229	229
Confidence Level(95.0%)	0.0076	0.0179

Table 25:Descriptive statistics of the DM market timing rule using A-REIT data

	Buy-and-hold	*DM rtn*
Mean	7.82E-05	0.0853
Standard Error	3.67E-03	0.0068
Median	5.42E-03	0.0584
Standard Deviation	5.55E-02	0.1023
Sample Variance	3.08E-03	0.0105
Kurtosis	1.96E+01	17.2195
Skewness	-3.02E+00	2.7757
Range	5.67E-01	0.9228
Minimum	-4.35E-01	-0.0142
Maximum	1.32E-01	0.9087
Sum	1.79E-02	19.5263
Count	229	229
Confidence Level(95.0%)	0.0072	0.0133

Table 26:Descriptive statistics of the DM market timing rule using Brazilian REIT data

	Buy-and-hold	*DM rtn*
Mean	0.0083	0.1255
Standard Error	0.0033	0.0137
Median	0.0130	0.0432
Standard Deviation	0.0344	0.1419
Sample Variance	0.0012	0.0201
Kurtosis	6.7671	-0.8935
Skewness	-1.4123	0.6023
Range	0.2736	0.5932
Minimum	-0.1725	-0.1026
Maximum	0.1010	0.4906
Sum	0.9016	13.5593
Count	108	108
Confidence Level(95.0%)	0.0066	0.0271

Table 27:Descriptive statistics of the DM market timing rule using SA REIT data

	Buy-and-hold	*DM rtn*
Mean	-0.0071	0.0593
Standard Error	0.0102	0.0103
Median	-0.0013	0.0168
Standard Deviation	0.0835	0.0844
Sample Variance	0.0070	0.0071
Kurtosis	18.7635	2.7539
Skewness	-3.0724	1.8408
Range	0.6754	0.3481
Minimum	-0.5027	-0.0187
Maximum	0.1727	0.3294
Sum	-0.4734	3.9700
Count	67	67
Confidence Level(95.0%)	0.0204	0.0206

Table 28: Descriptive statistics of the DM market timing rule using the Hypothetical Portfolio data

	Buy-and-hold	*DM rtn*
Mean	0.0065	0.1497
Standard Error	0.0037	0.0093
Median	0.0141	0.1328
Standard Deviation	0.0562	0.1404
Sample Variance	0.0032	0.0197
Kurtosis	9.8905	3.6531
Skewness	-1.9558	1.3312
Range	0.5577	0.8913
Minimum	-0.3446	-0.0184
Maximum	0.2131	0.8729
Sum	1.4856	34.2746
Count	229	229
Confidence Level(95.0%)	0.0073	0.0183

The average return under the DM market timing strategy is greater in every market than the mean return had the rule not been implemented. In every market, the average return from the strategy is closer to the minimum bound of the respective range of returns rather than the maximum. Specifically, the average return is highest in the US (15.6%), whereas this timing rule yields the lowest average return in SA (5.9%). These values are notably higher than seen under the other market timing rules. However, the DM returns also exhibit the mildest correlation against the returns of the actual indices. The higher returns and low correlation of returns is indicative of the constant switching between asset classes to achieve the highest yield possible.

The correlation of the returns achieved under DM market timing rule are presented in Figure 7 below:

	Lognormal rtn
Lognormal rtn	1
US returns	0.2193
JPY returns	0.253
UK returns	0.2578
Aus returns	0.1635
Brazil returns	0.3183
SA returns	0.1848
Hyp portfolio returns	0.2216

Figure 7:Correlation table of DM returns

While the switching between multiple asset classes may create some benefit of diversification under this strategy, it achieves this by bearing greater risk than simply remaining invested in the respective REIT index. The statistics indicate that the standard deviation of the DM portfolios are two to three times more than the standard deviation of the REIT indices.

The range of returns under the DM market timing rule have significantly less negative minimum returns compared to the minimum return of the buy-and-hold strategy. Further, the results also indicate that the maximum returns are significantly greater than the maximum returns of the buy-and-hold strategy. Specifically, this market timing rule yields the highest return in the US (110%) while it yields the lowest return in Australia (-1.4%) in any one month. In contrast to the former three strategies, the DM market timing rule generally outperforms the buy-and-hold strategy in most months while similar to the others, rarely underperforming the buy-and-hold strategy.

The statistics also indicate that DM returns are all positively skewed whereas the returns achieved by holding the REIT index are all negatively skewed. The DM market timing rule thus captures positive returns more frequently than the buy-and-hold strategy. Unlike the former timing rules, the kurtosis coefficients are lower under the DM timing rule than they are under the buy-and-hold strategy. This indicates that the returns achieved under the DM timing rule are less extreme than the actual returns. This is confirmed by the mean return being closer to the lower bound of the range of returns, as highlighted earlier. The JB and SW tests corroborates the kurtosis and skewness statistics.

5.2 Comparison of the predictive ability of the market timing rules

Market timing rules have been researched extensively, with investors favouring rules such as the MA and TSM because of their proven profitability. However, the results presented in section 5.1 of this study indicate that alternative strategies may also yield strong returns. Many of the studies reviewed in this study only examine the effectiveness of one strategy within a given asset class. However, Papadopoulos (2017) tests the effectiveness of three different market timing rules on stocks in the renewable energy sector. Of the three rules, the author finds the MA market timing rule to be most the most effective strategy for renewable energy stocks since it produces more positive signals compared to the remaining two strategies. All four market timing rules outperform the buy-and-hold strategy in this study. However, some rules, such as the DM market timing rules, yields greater returns than others, such as the MMAC market timing rule. It is therefore insightful to provide a comparison of the effectiveness of the four market timing rules implemented in this study.

The MA and TSM market timing rules perform similarly. The predictive power of these rules are positively correlated with an increase in the lengths of periods used to calculate the MA and TSM, respectively. This is seen in the decrease in sell signals as the lengths become greater. The TSM provides the advantage of capturing more of the positive returns compared to the MA. However, it is important to note that the positive returns being captured may largely be attributable to market shocks or bearish conditions, since this is where the TSM market timing rule yields optimal returns (Moskowitz, Ooi and Pederson, 2011). The MA market timing rule, as observed by the studies in chapter 2 of this study, provide a lower risk approach to achieving excess returns, since this rule smooths out the volatility in the prices of the indices. The results of this study indicate that on average, the standard deviations are lower under the MA rule compared to the TSM rule.

Similar to the TSM market timing rule, the MMAC market timing rule outperforms the buy-and-hold strategy. It also outperforms both the MA and the TSM. However, as a general rule with implementing market timing rules, this outperformance may not significant considering transaction costs and taxes which still need to be accounted. Like the TSM market timing rule, the MMAC market timing rule also tends to outperform during bearish market conditions and does so with lower risk when using indices to time the market instead of individual stocks.

The DM market timing rule yields the greatest range of risk-adjusted returns compared to the other three market timing rules implemented in this study. According to Tonnessen (2018), this is because the DM portfolio has to recoup less losses than the buy-and-hold strategy during periods of market recovery. This may also be attributable to the use of longer lookback periods as opposed to the former three strategies which tend to perform well during shorter lookback periods. The contrarian theme of the DM market timing rule provides an overall lower standard deviation since it rotates between more than two assets to achieve the maximum return. Unlike the former market timing rules, this rule provides optimal returns during bull markets. As highlighted by Papadopoulos (2017), the appropriateness of a market timing rule is dependent on the prevailing market cycle.

5.3 Effectiveness of the market timing rules during market crises

The market timing rules have displayed a general outperformance relative to their respective buy-and-hold strategies. However, a crucial part to this study is to examine the effectiveness of these rules during periods of market crisis to determine whether these rules still retain their accuracy and repeatability. The studies of De Chassart (2002), Bird, Gao and Yeung (2017), and Anghel (2013) are some that highlight that market timing rules are more effective in certain market conditions compared to others.

5.3.1 The GFC

The GFC was characterised by a unanimous contraction in global markets over the period 16 September 2007 to 31 March 2009. Huerta, Egly, and Escobari (2015) found that the GFC restricted the ability of REITs to raise funds through debt and equity markets. The authors found that the restricted access to liquidity caused by the GFC resulted in sharp declines in REITs' security returns with simultaneous spikes in their volatility. The MA descriptive statistics during the GFC are shown in tables 29-33 below:

Table 29:MA descriptive statistics during GFC using US REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0512	0.0232	0.0197	0.0111	0.0100	0.0068	0.0043
Standard Error	0.0312	0.0091	0.0092	0.0047	0.0047	0.0036	0.0030
Median	-0.0014	0.0025	0.0015	0.0015	0.0014	0.0014	0.0014
Standard Deviation	0.1360	0.0396	0.0400	0.0206	0.0205	0.0159	0.0132
Sample Variance	0.0185	0.0016	0.0016	0.0004	0.0004	0.0003	0.0002
Kurtosis	0.7077	8.2972	9.0090	2.4013	3.0599	7.2547	18.7358
Skewness	-1.0323	2.6618	2.8478	1.9100	2.1028	2.8177	4.3160
Range	0.5447	0.1618	0.1633	0.0651	0.0651	0.0587	0.0587
Minimum	-0.3828	0.0000	-0.0014	-0.0014	-0.0014	0.0000	0.0000
Maximum	0.1619	0.1619	0.1619	0.0637	0.0637	0.0587	0.0587
Sum	-0.9726	0.4417	0.3737	0.2118	0.1903	0.1297	0.0814
Count	19	19	19	19	19	19	19
Confidence	0.0655	0.0191	0.0193	0.0099	0.0099	0.0077	0.0064

Table 30:MA descriptive statistics during the GFC using J-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0395	0.0143	0.0120	0.0023	0.0023	0.0004	0.0004
Standard Error	0.0195	0.0060	0.0060	0.0019	0.0019	0.0000	0.0000
Median	-0.0344	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
Standard Deviation	0.0850	0.0260	0.0261	0.0083	0.0083	0.0001	0.0001
Sample Variance	0.0072	0.0007	0.0007	0.0001	0.0001	0.0000	0.0000
Kurtosis	0.4594	5.5527	6.3918	18.9707	18.9921	-0.0763	-0.0763
Skewness	-0.7661	2.2835	2.4985	4.3540	4.3576	-1.2670	-1.2670
Range	0.3410	0.0985	0.0992	0.0371	0.0365	0.0003	0.0003
Minimum	-0.2423	0.0002	-0.0004	-0.0004	0.0002	0.0002	0.0002
Maximum	0.0988	0.0988	0.0988	0.0367	0.0367	0.0005	0.0005
Sum	-0.7495	0.2710	0.2287	0.0432	0.0439	0.0077	0.0077
Count	19	19	19	19	19.	19	19.
Confidence	0.0410	0.0125	0.0126	0.0040	0.0040	0.0001	0.0001

Table 31:MA descriptive statistics during the GFC using UK REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0675	0.0073	0.0043	0.0018	0.0003	0.0003	0.0003
Standard Error	0.0203	0.0038	0.0038	0.0029	0.0003	0.0003	0.0003
Median	-0.0510	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Standard Deviation	0.0885	0.0167	0.0166	0.0128	0.0011	0.0011	0.0011
Sample Variance	0.0078	0.0003	0.0003	0.0002	0.0000	0.0000	0.0000
Kurtosis	0.2595	3.2267	5.1936	13.3713	19.0000	19.0000	19.0000
Skewness	-0.8266	2.1569	2.2192	3.0438	4.3589	4.3589	4.3589
Range	0.3052	0.0506	0.0717	0.0717	0.0049	0.0049	0.0049
Minimum	-0.2547	0.0000	-0.0212	-0.0212	0.0000	0.0000	0.0000
Maximum	0.0506	0.0506	0.0506	0.0506	0.0049	0.0049	0.0049
Sum	-1.2831	0.1386	0.0823	0.0343	0.0049	0.0049	0.0049
Count	19	19	19	19	19.	19	19.
Confidence	0.0427	0.0080	0.0080	0.0062	0.0005	0.0005	0.0005

Table 32:MA descriptive statistics during the GFC using A-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0681	0.0078	0.0073	0.0073	0.0007	0.0007	0.0007
Standard Error	0.0205	0.0049	0.0049	0.0049	0.0011	0.0011	0.0011
Median	-0.0637	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Standard Deviation	0.0895	0.0213	0.0215	0.0215	0.0047	0.0047	0.0047
Sample Variance	0.0080	0.0005	0.0005	0.0005	0.0000	0.0000	0.0000
Kurtosis	0.8714	10.2641	10.0588	10.0588	15.2930	15.2930	15.2930
Skewness	-0.6733	3.1564	3.1171	3.1171	3.5560	3.5560	3.5560
Range	0.3764	0.0848	0.0912	0.0912	0.0256	0.0256	0.0256
Minimum	-0.2916	0.0000	-0.0064	-0.0064	-0.0064	-0.0064	-0.0064
Maximum	0.0848	0.0848	0.0848	0.0848	0.0192	0.0192	0.0192
Sum	-1.2931	0.1482	0.1394	0.1394	0.0129	0.0129	0.0129
Count	19	19	19	19	19	19	19
Confidence	0.0431	0.0103	0.0104	0.0104	0.0023	0.0023	0.0023

Table 33:MA descriptive statistics during the GFC using the Hypothetical Portfolio data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0530	0.0161	0.0063	0.0042	0.0023	0.0025	0.0011
Standard Error	0.0263	0.0063	0.0032	0.0033	0.0023	0.0023	0.0002
Median	-0.0186	0.0020	0.0012	0.0012	0.0010	0.0012	0.0012
Standard Deviation	0.1146	0.0274	0.0139	0.0144	0.0100	0.0100	0.0007
Sample Variance	0.0131	0.0007	0.0002	0.0002	0.0001	0.0001	0.0000
Kurtosis	1.1793	8.3099	1.8439	2.5890	14.8346	14.7703	-0.5997
Skewness	-1.1834	2.6504	1.5909	1.5153	3.4641	3.4397	0.5135
Range	0.4636	0.1117	0.0542	0.0599	0.0542	0.0542	0.0023
Minimum	-0.3517	0.0002	-0.0129	-0.0186	-0.0129	-0.0129	0.0001
Maximum	0.1119	0.1119	0.0413	0.0413	0.0413	0.0413	0.0025
Sum	-1.0077	0.3057	0.1200	0.0796	0.0429	0.0468	0.0208
Count	19	19	19	19	19	19	19
Confidence	0.0553	0.0132	0.0067	0.0070	0.0048	0.0048	0.0004

Note, REIT regimes were only incepted in SA and Brazil after the GFC. Hence, analysis for these markets have not been included for the GFC period.

In line with the findings of Huerta, Egly, and Escobari (2015), the average returns achieved under the MA market timing rule were consistently lower than the average MA returns discussed in section 5.1.1 of this study[16]. The lowest average MA return is found in Japan over the 6-month MA period (0.04%) while the highest average MA return is found in the US over the 2-month MA period (2.3%). During this crisis period, the average return of the buy-and-hold strategy was negative in every market, with Australian buy-and-hold strategy yielding the greatest negative average MA return (-6.8%). The unanimous negative return performance is explained by Chang and Cheng (2014) in section 2.2.2 who assert that market panic increases the contagion effect between REIT markets. Therefore, if the returns of REITs deteriorate in one market, REITs' returns are bound to deteriorate in other markets as well. Despite the MA market timing rule

[16] No comparable results were found for Brazil and SA during the GFC since the data for the relevant indices are only available from 2011 and 2014, respectively.

underperforming in the GFC relative to the overall performance, it still outperforms the buy-and-hold strategy. This indicates that the market timing ability of the MA rule persists during crisis periods.

Boudry et. al (2012) observe that REITs' securities tend to behave more like equity than bonds during market crises. Hence, they should experience greater volatility (Huerta, Egly & Escobari, 2015). The standard deviation of returns of the buy-and-hold strategy ranges from 8.5% to 13.6% across the various markets during the GFC. This is an increase from standard deviation of 5.4% to 6.4% which is observed over the entire sample period. During the crisis, the MA results indicate reduced volatility (i.e. extremely close to 0%) as measured by standard deviation and a tighter range in returns compared to the standard deviations of the respective buy-and-hold strategies. The reduced volatility further indicates that the market timing ability of this rule persisted throughout the GFC. The TSM descriptive statistics during the GFC are shown in tables 34-38 below:

Table 34:TSM descriptive statistics during the GFC using US REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0512	0.0067	-0.0068	-0.0022	0.0023	0.0013	-0.0048
Standard Error	0.0312	0.0037	0.0087	0.0066	0.0012	0.0002	0.0065
Median	-0.0014	0.0014	0.0011	0.0011	0.0014	0.0014	0.0007
Standard Deviation	0.1360	0.0159	0.0381	0.0288	0.0051	0.0010	0.0282
Sample Variance	0.0185	0.0003	0.0015	0.0008	0.0000	0.0000	0.0008
Kurtosis	0.7077	7.2149	5.0925	15.6040	16.7026	-0.6281	7.6061
Skewness	-1.0323	2.8085	-2.0302	-3.7016	3.9771	0.5415	-2.3581
Range	0.5447	0.0601	0.1748	0.1472	0.0243	0.0032	0.1421
Minimum	-0.3828	-0.0014	-0.1161	-0.1161	-0.0014	0.0000	-0.0996
Maximum	0.1619	0.0587	0.0587	0.0311	0.0229	0.0032	0.0425
Sum	-0.9726	0.1277	-0.1294	-0.0421	0.0437	0.0242	-0.0914
Count	19	19	19	19	19	19	19
Confidence	0.0655	0.0077	0.0184	0.0139	0.0025	0.0005	0.0136

Table 35:TSM descriptive statistics during the GFC using J-REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0395	-0.0028	0.0004	0.0004	0.0004	0.0023	-0.0132
Standard Error	0.0195	0.0055	0.0000	0.0000	0.0000	0.0019	0.0104
Median	-0.0344	0.0005	0.0005	0.0005	0.0005	0.0005	0.0003
Standard Deviation	0.0850	0.0238	0.0001	0.0001	0.0001	0.0081	0.0453
Sample Variance	0.0072	0.0006	0.0000	0.0000	0.0000	0.0001	0.0020
Kurtosis	0.4594	14.4061	-0.0763	-0.0763	-0.0763	18.9915	8.6423
Skewness	-0.7661	-3.3132	-1.2670	-1.2670	-1.2670	4.3575	-2.6698
Range	0.3410	0.1316	0.0003	0.0003	0.0003	0.0357	0.2083
Minimum	-0.2423	-0.0950	0.0002	0.0002	0.0002	0.0002	-0.1725
Maximum	0.0988	0.0367	0.0005	0.0005	0.0005	0.0359	0.0359
Sum	-0.7495	-0.0522	0.0077	0.0077	0.0077	0.0431	-0.2516
Count	19	19	19	19	19	19	19
Confidence	0.0410	0.0115	0.0001	0.0001	0.0001	0.0039	0.0218

Table 36:TSM descriptive statistics during the GFC using UK REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0675	-0.0035	0.0043	0.0018	0.0003	0.0003	-0.0115
Standard Error	0.0203	0.0029	0.0038	0.0029	0.0003	0.0003	0.0069
Median	-0.0510	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Standard Deviation	0.0885	0.0125	0.0166	0.0128	0.0011	0.0011	0.0300
Sample Variance	0.0078	0.0002	0.0003	0.0002	0.0000	0.0000	0.0009
Kurtosis	0.2595	12.6250	5.1936	13.3713	19.0000	19.0000	5.1826
Skewness	-0.8266	-3.4889	2.2192	3.0438	4.3589	4.3589	-2.4891
Range	0.3052	0.0559	0.0717	0.0717	0.0049	0.0049	0.1049
Minimum	-0.2547	-0.0510	-0.0212	-0.0212	0.0000	0.0000	-0.1000
Maximum	0.0506	0.0049	0.0506	0.0506	0.0049	0.0049	0.0049
Sum	-1.2831	-0.0673	0.0823	0.0343	0.0049	0.0049	-0.2184
Count	19	19	19	19	19	19	19
Confidence	0.0427	0.0060	0.0080	0.0062	0.0005	0.0005	0.0145

Table 37:TSM descriptive statistics during the GFC using A-REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0681	-0.0027	-0.0038	-0.0035	0.0000	0.0007	-0.0184
Standard Error	0.0205	0.0036	0.0034	0.0035	0.0000	0.0011	0.0096
Median	-0.0637	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Standard Deviation	0.0895	0.0155	0.0150	0.0150	0.0000	0.0047	0.0418
Sample Variance	0.0080	0.0002	0.0002	0.0002	0.0000	0.0000	0.0017
Kurtosis	0.8714	15.3231	18.5807	19.0000	0.0000	15.2930	4.7736
Skewness	-0.6733	-3.6010	-4.2946	-4.3589	0.0000	3.5560	-2.2062
Range	0.3764	0.0829	0.0656	0.0656	0.0000	0.0256	0.1692
Minimum	-0.2916	-0.0637	-0.0656	-0.0656	0.0000	-0.0064	-0.1500
Maximum	0.0848	0.0192	0.0000	0.0000	0.0000	0.0192	0.0192
Sum	-1.2931	-0.0508	-0.0719	-0.0656	0.0000	0.0129	-0.3502
Count	19	19	19	19	19	19	19
Confidence	0.0431	0.0075	0.0072	0.0072	0.0000	0.0023	0.0202

Table 38:TSM descriptive statistics during the GFC using the Hypothetical Portfolio data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0530	0.0023	-0.0058	0.0011	0.0011	0.0011	-0.0088
Standard Error	0.0263	0.0028	0.0061	0.0002	0.0002	0.0002	0.0058
Median	-0.0186	0.0010	0.0010	0.0012	0.0012	0.0012	0.0004
Standard Deviation	0.1146	0.0122	0.0268	0.0007	0.0007	0.0007	0.0252
Sample Variance	0.0131	0.0001	0.0007	0.0000	0.0000	0.0000	0.0006
Kurtosis	1.1793	6.1308	18.3256	-0.5997	-0.5997	-0.5997	6.1790
Skewness	-1.1834	1.9022	-4.2563	0.5135	0.5135	0.5135	-2.3215
Range	0.4636	0.0599	0.1180	0.0023	0.0023	0.0023	0.1146
Minimum	-0.3517	-0.0186	-0.1155	0.0001	0.0001	0.0001	-0.0917
Maximum	0.1119	0.0413	0.0025	0.0025	0.0025	0.0025	0.0229
Sum	-1.0077	0.0442	-0.1102	0.0208	0.0208	0.0208	-0.1673
Count	19	19	19	19	19	19	19
Confidence	0.0553	0.0059	0.0129	0.0004	0.0004	0.0004	0.0122

The average TSM returns during the GFC are consistently lower than the average TSM returns discussed in section 5.1.2 of this study. The lowest average TSM return is found in the UK over the 6-month period (0.03%) while the highest average TSM return is found in the US over the 2-month period (0.7%). Evidently, the average returns achieved under the TSM market timing rule are mostly marginally above 0% or negative during the GFC. Although marginal outperformance of the buy-and-hold strategy is observed, the results strongly contrast Qin, Pan and Bai (2020) and Li, Sakkas and Urquhart (2021) who find that the TSM market timing rule performs well during bearish market conditions.

The TSM market timing rule generally provides lower dispersion of returns (i.e. extremely close to 0%) which indicates reduced volatility as measured by standard deviation and a tighter range in returns. The reduced volatility is attributable to the switches to a portfolio of T-Bills which protects the investor from downside risk. Therefore, as with the MA market timing rule, the TSM market timing rule retains its market timing ability.

Table 39:MMAC descriptive statistics during the GFC using US REIT data

	Buy-and-hold	*MMAC rtn*
Mean	-0.0512	0.0155
Standard Error	0.0312	0.0036
Median	-0.0014	0.0135
Standard Deviation	0.1360	0.0156
Sample Variance	0.0185	0.0002
Kurtosis	0.7077	2.5460
Skewness	-1.0323	1.4739
Range	0.5447	0.0601
Minimum	-0.3828	0.0003
Maximum	0.1619	0.0604
Sum	-0.9726	0.2938
Count	19	19
Confidence	0.0655	0.0075

Table 40:MMAC descriptive statistics during the GFC using J-REIT data

	Buy-and-hold	*MMAC rtn*
Mean	-0.0395	0.0048
Standard Error	0.0195	0.0003
Median	-0.0344	0.0056
Standard Deviation	0.0850	0.0014
Sample Variance	0.0072	0.0000
Kurtosis	0.4594	-0.0763
Skewness	-0.7661	-1.2670
Range	0.3410	0.0039
Minimum	-0.2423	0.0020
Maximum	0.0988	0.0059
Sum	-0.7495	0.0919
Count	19	19
Confidence	0.0410	0.0007

Table 41:MMAC descriptive statistics during the GFC using UK REIT data

	Buy-and-hold	*MMAC rtn*
Mean	-0.0675	0.0031
Standard Error	0.0203	0.0031
Median	-0.0510	0.0000
Standard Deviation	0.0885	0.0135
Sample Variance	0.0078	0.0002
Kurtosis	0.2595	19.0000
Skewness	-0.8266	4.3589
Range	0.3052	0.0587
Minimum	-0.2547	0.0000
Maximum	0.0506	0.0587
Sum	-1.2831	0.0587
Count	19	19
Confidence	0.0427	0.0065

Table 42:MMAC descriptive statistics during the GFC using A-REIT data

	Buy-and-	*MMAC*
Mean	-0.0681	0.0575
Standard Error	0.0205	0.0056
Median	-0.0637	0.0712
Standard Deviation	0.0895	0.0246
Sample Variance	0.0080	0.0006
Kurtosis	0.8714	0.8509
Skewness	-0.6733	-1.2245
Range	0.3764	0.0843
Minimum	-0.2916	-0.0063
Maximum	0.0848	0.0780
Sum	-1.2931	1.0928
Count	19	19
Confidence	0.0431	0.0119

Table 43:MMAC descriptive statistics during the GFC using the Hypothetical Portfolio data

	Buy-and-hold	*MMAC rtn*
Mean	-0.0530	0.0157
Standard Error	0.0263	0.0021
Median	-0.0186	0.0170
Standard Deviation	0.1146	0.0093
Sample Variance	0.0131	0.0001
Kurtosis	1.1793	-0.7581
Skewness	-1.1834	0.3707
Range	0.4636	0.0290
Minimum	-0.3517	0.0037
Maximum	0.1119	0.0327
Sum	-1.0077	0.2986
Count	19	19
Confidence Level(95.0%)	0.0553	0.0045

The average MMAC returns are consistently lower during the period of the GFC compared to the average MMAC returns achieved in section 5.1.3. The lowest average MMAC return during the crisis is found in the UK (0.3%) while the highest average MMAC returns during the crisis is found in the global portfolio (1.6%). Consistent with the results of the previous market timing rules, the MMAC market timing rule still manages to outperform the buy-and-hold strategy during the GFC. This outperformance is consistent with the findings of Patari and Vilka (2014) who find that MMAC rules based on both individual stocks and indices outperform a buy-and-hold strategy during bearish market conditions. The weaker outperformance may also be attributable to the increase in the dispersion of returns, since the standard deviation associated with this rule increases during the period of the GFC. Although the MMAC returns were lower during the crisis, the rule still retained its ability to time the market.

The average DM returns are also consistently lower during the period of the GFC compared to the average returns for the entire sample period as outline in section 5.1.4. The lowest average return during the crisis is found in the UK (-0.1%) while the highest average return during the crisis is found in Japan (2.8%). However, the DM market timing rule continued to outperform the buy-and-hold strategy in every market, with the buy-and-hold strategy achieving negative average returns in every market. The resilient performance of the DM rule is consistent with Antonacci (2014) who finds that outperformance under this rule persists throughout severe economic stress. The DM descriptive statistics during the GFC are shown in tables 44-48 below:

Table 44:DM descriptive statistics during the GFC using US REIT data

	Buy-and-hold	*DM rtn*
Mean	-0.0512	0.0078
Standard Error	0.0312	0.0042
Median	-0.0014	0.0028
Standard Deviation	0.1360	0.0185
Sample Variance	0.0185	0.0003
Kurtosis	0.7077	0.2964
Skewness	-1.0323	0.7807
Range	0.5447	0.0701
Minimum	-0.3828	-0.0234
Maximum	0.1619	0.0467
Sum	-0.9726	0.1479
Count	19	19
Confidence	0.0655	0.0089

Table 45:DM descriptive statistics during the GFC using J-REIT data

	Buy-and-	*DM rtn*
Mean	-0.0395	0.0281
Standard Error	0.0195	0.0168
Median	-0.0344	0.0036
Standard Deviation	0.0850	0.0731
Sample Variance	0.0072	0.0053
Kurtosis	0.4594	8.0432
Skewness	-0.7661	2.8902
Range	0.3410	0.2889
Minimum	-0.2423	-0.0127
Maximum	0.0988	0.2761
Sum	-0.7495	0.5344
Count	19	19
Confidence	0.0410	0.0352

Table 46:DM descriptive statistics during the GFC using UK REIT data

	Buy-and-hold	*DM rtn*
Mean	-0.0675	-0.0013
Standard Error	0.0203	0.0047
Median	-0.0510	-0.0011
Standard Deviation	0.0885	0.0204
Sample Variance	0.0078	0.0004
Kurtosis	0.2595	1.0809
Skewness	-0.8266	-0.7987
Range	0.3052	0.0785
Minimum	-0.2547	-0.0482
Maximum	0.0506	0.0303
Sum	-1.2831	-0.0250
Count	19	19
Confidence	0.0410	0.0352

Table 47:DM descriptive statistics during the GFC using A-REIT data

	Buy-and-	*DM rtn*
Mean	-0.0681	0.0215
Standard Error	0.0205	0.0091
Median	-0.0637	0.0110
Standard Deviation	0.0895	0.0396
Sample Variance	0.0080	0.0016
Kurtosis	0.8714	5.2979
Skewness	-0.6733	2.4218
Range	0.3764	0.1501
Minimum	-0.2916	-0.0132
Maximum	0.0848	0.1369
Sum	-1.2931	0.4079
Count	19	19
Confidence	0.0431	0.0191

Table 48:DM descriptive statistics during the GFC using the Hypothetical Portfolio data

	Buy-and-hold	*DM rtn*
Mean	-0.0505	0.0069
Standard Error	0.0260	0.0037
Median	-0.0231	0.0024
Standard Deviation	0.1134	0.0162
Sample Variance	0.0129	0.0003
Kurtosis	1.1755	0.8525
Skewness	-1.1329	0.9799
Range	0.4652	0.0641
Minimum	-0.3446	-0.0184
Maximum	0.1206	0.0457
Sum	-0.9594	0.1305
Count	19	19
Confidence	0.0547	0.0078

The DM market timing rule significantly contributes to reducing the risk assumed in achieving the DM returns, since the results indicate that the standard deviation is lower for all markets when compared to the results presented in section 5.1.4. Antonacci (2014) attributes this to the strategy correctly identifying positive absolute momentum, which aids DM portfolios in recouping less losses during periods of market recovery.

Evidently, the US REIT market shows the greatest resilience since the highest average returns are mostly achieved in this market for all the timing rules. The global portfolio provides the highest reduction in overall portfolio risk, which is attributable to the diversification benefits that it exhibits. It can be concluded that market timing ability weakens during periods of crisis but still outperforms the buy-and-hold strategy, with the DM market timing rule yielding the highest returns.

5.3.2 The ESDC

As explained previously, the ESDC was characterised by the combination of collapsing European financial institutions, excessive public debt, and a significant rise in the long-term bond yield spreads of government securities (Kenton, 2020). The period of the crisis is 23 April 2010 to 06 September 2012[17]. The MA descriptive statistics during the ESDC are shown in tables 49-53 below:

Table 49:MA descriptive statistics during the ESDC using US REIT data

	Lonormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0126	0.029	0.0247	0.0229	0.0229	0.0214	0.0177
Standard Error	0.0096	0.0061	0.0068	0.0073	0.0073	0.0076	0.0084
Median	0.0176	0.0176	0.0165	0.0165	0.0176	0.0176	0.0176
Standard Deviation	0.0527	0.0334	0.0374	0.0400	0.0400	0.0418	0.0459
Sample Variance	0.0028	0.0011	0.0014	0.0016	0.0016	0.0018	0.0021
Kurtosis	0.2554	2.0227	1.1065	0.8673	0.8078	0.5334	0.0343
Skewness	-0.1445	1.3132	0.8887	0.5884	0.5802	0.4648	0.2739
Range	0.2504	0.1346	0.1728	0.1901	0.1901	0.1901	0.1916
Minimum	-0.1157	0.0000	-0.0382	-0.0555	-0.0555	-0.0555	-0.0570
Maximum	0.1347	0.1347	0.1347	0.1347	0.1347	0.1347	0.1347
Sum	0.3766	0.8553	0.7418	0.6862	0.6877	0.6410	0.5305
Count	30	30	30	30	30	30	30
Confidence Level(95.0%)	0.0197	0.0125	0.0140	0.0149	0.0150	0.0156	0.0171

[17] Partial comparative results were found for Brazil during the crisis since the start date of the data is 31 January 2011. No comparative results were found for SA during this crisis as the return data is only available from 30 June 2014 in this market.

Table 50:MA descriptive statistics during the ESDC using J-REIT data

	Lonormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0065	0.022	0.0200	0.0174	0.0182	0.0167	0.0158
Standard Error	0.0087	0.0059	0.0062	0.0062	0.0061	0.0064	0.0070
Median	-0.0052	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Standard Deviation	0.0475	0.0322	0.0339	0.0337	0.0332	0.0349	0.0383
Sample Variance	0.0023	0.0010	0.0011	0.0011	0.0011	0.0012	0.0015
Kurtosis	0.0937	2.6013	2.1143	2.7699	2.9419	2.4674	1.1814
Skewness	0.4471	1.6306	1.4897	1.7079	1.7535	1.4524	0.9707
Range	0.2095	0.1239	0.1415	0.1415	0.1415	0.1666	0.1675
Minimum	-0.0856	0.0001	-0.0176	-0.0176	-0.0176	-0.0427	-0.0436
Maximum	0.1239	0.1239	0.1239	0.1239	0.1239	0.1239	0.1239
Sum	0.1954	0.6713	0.6009	0.5232	0.5447	0.5020	0.4750
Count	30	30	30	30	30	30	30
Confidence Level(95.0%)	0.0177	0.0120	0.0127	0.0126	0.0124	0.0130	0.0143

Table 51:MA descriptive statistics during the ESDC using UK REIT data

	Lonormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0021	0.022	0.0193	0.0176	0.0137	0.0102	0.0097
Standard Error	0.0094	0.0050	0.0056	0.0053	0.0055	0.0057	0.0056
Median	0.0036	0.0036	0.0036	0.0018	0.0005	0.0005	0.0005
Standard Deviation	0.0512	0.0275	0.0308	0.0290	0.0304	0.0313	0.0307
Sample Variance	0.0026	0.0008	0.0009	0.0008	0.0009	0.0010	0.0009
Kurtosis	-0.5318	-1.0097	-1.0577	-0.7659	0.2138	0.1469	0.3899
Skewness	-0.4042	0.7955	0.5234	0.7442	0.3290	0.4326	0.5500
Range	0.1929	0.0788	0.1056	0.0985	0.1377	0.1377	0.1377
Minimum	-0.1139	0.0002	-0.0266	-0.0195	-0.0587	-0.0587	-0.0587
Maximum	0.0790	0.0790	0.0790	0.0790	0.0790	0.0790	0.0790
Sum	0.0637	0.6688	0.5785	0.5267	0.4109	0.3049	0.2904
Count	30	30	30	30	30	30	30
Confidence Level(95.0%)	0.0191	0.0103	0.0115	0.0108	0.0113	0.0117	0.0115

Table 52:MA descriptive statistics during the ESDC using A-REIT data

	Lonormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0022	0.014	0.0114	0.0104	0.0091	0.0094	0.0061
Standard Error	0.0057	0.0033	0.0036	0.0038	0.0037	0.0036	0.0030
Median	0.0005	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000
Standard Deviation	0.0310	0.0180	0.0196	0.0206	0.0202	0.0199	0.0166
Sample Variance	0.0010	0.0003	0.0004	0.0004	0.0004	0.0004	0.0003
Kurtosis	-0.3226	0.1945	-0.0062	-0.1416	0.3136	0.3840	3.4129
Skewness	-0.2138	1.1539	0.9997	0.8542	1.0270	1.0467	1.9495
Range	0.1228	0.0545	0.0683	0.0754	0.0754	0.0754	0.0683
Minimum	-0.0684	0.0000	-0.0139	-0.0209	-0.0209	-0.0209	-0.0139
Maximum	0.0545	0.0545	0.0545	0.0545	0.0545	0.0545	0.0545
Sum	0.0656	0.4079	0.3421	0.3132	0.2735	0.2832	0.1823
Count	30	30	30	30	30	30	30
Confidence Level(95.0%)	0.0116	0.0067	0.0073	0.0077	0.0075	0.0074	0.0062

Table 53:Descriptive statistics during the ESDC using the Hypothetical Portfolio data

	Lonormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0210	0.024	0.0218	0.0218	0.0218	0.0218	0.0218
Standard Error	0.0041	0.0033	0.0039	0.0039	0.0039	0.0039	0.0039
Median	0.0175	0.0175	0.0175	0.0175	0.0175	0.0175	0.0175
Standard Deviation	0.0181	0.0145	0.0172	0.0172	0.0172	0.0172	0.0172
Sample Variance	0.0003	0.0002	0.0003	0.0003	0.0003	0.0003	0.0003
Kurtosis	-0.4720	0.0702	-0.2436	-0.2436	-0.2436	-0.2436	-0.2436
Skewness	0.1703	0.8479	0.2373	0.2373	0.2373	0.2373	0.2373
Range	0.0648	0.0523	0.0648	0.0648	0.0648	0.0648	0.0648
Minimum	-0.0056	0.0069	-0.0056	-0.0056	-0.0056	-0.0056	-0.0056
Maximum	0.0592	0.0592	0.0592	0.0592	0.0592	0.0592	0.0592
Sum	0.4210	0.4760	0.4367	0.4367	0.4367	0.4367	0.4367
Count	30	30	30	30	30	30	30
Confidence Level(95.0%)	0.0085	0.0068	0.0081	0.0081	0.0081	0.0081	0.0081

Note, REIT regimes were only incepted in SA after the ESDC. Hence, analysis has not been included for the ESDC period.

The average MA returns during the crisis period remained in line with the average MA returns presented in section 5.1.1 of this study. In markets such as the US, Japan and the global portfolio, the average MA returns were higher than the average MA returns in section 5.1.1. Brazil and SA average returns underperformed the buy-and-hold strategy, with returns diminishing as the MA periods increased. Therefore, the diminishing average MA returns for Brazil and SA during the ESDC are consistent with Abuzayed, Al-Fayoumi and Bouri (2020) who find that REITs lose their ability to yield any significant returns during a crisis. The highest average return is found in the US (2.9%) while the lowest average return is found in Australia (0.6%).

Abuzayed, Al-Fayoumi and Bouri (2020) find that REITs typically provide downside risk protection during market crises. The standard deviation of returns of the buy-and hold strategy range from 1.8% to 5.3% during the ESDC. During the crisis, the MA results indicate a reduced standard deviation range (1.5% to 5.1%). The reduced volatility together with outperformance of the TSM (except Brazil and SA), indicate that the MA provides market timing ability that persists during this crisis. The TSM descriptive statistics during the ESDC are shown in tables 54-59 below:

Table 54:TSM descriptive statistics during the ESDC using US REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0126	0.011	0.0155	0.0117	0.0057	0.0106	0.0103
Standard Error	0.0096	0.0061	0.0069	0.0073	0.0082	0.0092	0.0094
Median	0.0176	0.0001	0.0146	0.0067	0.0000	0.0068	0.0146
Standard Deviation	0.0527	0.0333	0.0380	0.0399	0.0450	0.0507	0.0517
Sample Variance	0.0028	0.0011	0.0014	0.0016	0.0020	0.0026	0.0027
Kurtosis	0.2554	-0.7827	-0.6434	-0.7668	0.4711	0.7706	0.4655
Skewness	-0.1445	-0.0663	-0.1233	-0.0436	-0.4938	-0.0457	-0.0586
Range	0.2504	0.1237	0.1481	0.1496	0.2084	0.2504	0.2504
Minimum	-0.1157	-0.0555	-0.0555	-0.0570	-0.1157	-0.1157	-0.1157
Maximum	0.1347	0.0682	0.0927	0.0927	0.0927	0.1347	0.1347
Sum	0.3766	0.3239	0.4650	0.3502	0.1718	0.3176	0.3085
Count	30	30	30	30	30	30	30
Confidence	0.0197	0.0124	0.0142	0.0149	0.0168	0.0189	0.0193

Table 55:TSM descriptive statistics during the ESDC using J-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0065	0.013	0.0111	0.0078	0.0051	0.0042	0.0030
Standard Error	0.0087	0.0070	0.0076	0.0067	0.0068	0.0067	0.0080
Median	-0.0052	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Standard Deviation	0.0475	0.0383	0.0418	0.0367	0.0371	0.0369	0.0440
Sample Variance	0.0023	0.0015	0.0017	0.0013	0.0014	0.0014	0.0019
Kurtosis	0.0937	2.8318	1.5116	1.0575	0.9588	1.0162	1.3629
Skewness	0.4471	0.7861	0.5445	0.0600	0.2232	0.2496	0.7751
Range	0.2095	0.2095	0.2095	0.1844	0.1844	0.1844	0.2095
Minimum	-0.0856	-0.0856	-0.0856	-0.0856	-0.0856	-0.0856	-0.0856
Maximum	0.1239	0.1239	0.1239	0.0988	0.0988	0.0988	0.1239
Sum	0.1954	0.3989	0.3338	0.2331	0.1515	0.1260	0.0901
Count	30	30	30	30	30	30	30
Confidence	0.0177	0.0143	0.0156	0.0137	0.0138	0.0138	0.0164

Table 56:TSM descriptive statistics during the ESDC using UK REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0021	0.007	0.0193	0.0176	0.0137	-0.0004	0.0049
Standard Error	0.0094	0.0057	0.0056	0.0053	0.0055	0.0077	0.0084
Median	0.0036	0.0005	0.0036	0.0018	0.0005	0.0004	0.0004
Standard Deviation	0.0512	0.0315	0.0308	0.0290	0.0304	0.0419	0.0462
Sample Variance	0.0026	0.0010	0.0009	0.0008	0.0009	0.0018	0.0021
Kurtosis	-0.5318	0.2804	-1.0577	-0.7659	0.2138	1.7491	0.5558
Skewness	-0.4042	0.5898	0.5234	0.7442	0.3290	-0.6129	-0.5729
Range	0.1929	0.1377	0.1056	0.0985	0.1377	0.1929	0.1929
Minimum	-0.1139	-0.0587	-0.0266	-0.0195	-0.0587	-0.1139	-0.1139
Maximum	0.0790	0.0790	0.0790	0.0790	0.0790	0.0790	0.0790
Sum	0.0637	0.2234	0.5785	0.5267	0.4109	-0.0125	0.1456
Count	30	30	30	30	30	30	30
Confidence	0.0191	0.0118	0.0115	0.0108	0.0113	0.0157	0.0173

Table 57:TSM descriptive statistics during the ESDC using A-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0022	0.004	0.0043	0.0044	0.0043	0.0031	0.0009
Standard Error	0.0057	0.0040	0.0038	0.0035	0.0031	0.0035	0.0018
Median	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Standard Deviation	0.0310	0.0221	0.0206	0.0189	0.0171	0.0190	0.0099
Sample Variance	0.0010	0.0005	0.0004	0.0004	0.0003	0.0004	0.0001
Kurtosis	-0.3226	1.0655	2.2659	2.9285	3.7944	3.1593	2.3912
Skewness	-0.2138	0.3228	1.0155	1.7380	1.9219	1.0572	0.5862
Range	0.1228	0.0975	0.0975	0.0766	0.0766	0.0970	0.0462
Minimum	-0.0684	-0.0431	-0.0431	-0.0222	-0.0222	-0.0426	-0.0209
Maximum	0.0545	0.0545	0.0545	0.0545	0.0545	0.0545	0.0253
Sum	0.0656	0.1152	0.1287	0.1331	0.1292	0.0925	0.0258
Count	30	30	30	30	30	30	30
Confidence	0.0116	0.0083	0.0077	0.0071	0.0064	0.0071	0.0037

Table 58:TSM descriptive statistics during the ESDC using Brazilian REIT dat

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0210	0.021	0.0210	0.0210	0.0210	0.0210	0.0136
Standard Error	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0021
Median	0.0175	0.0175	0.0175	0.0175	0.0175	0.0175	0.0085
Standard Deviation	0.0181	0.0181	0.0181	0.0181	0.0181	0.0181	0.0096
Sample Variance	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0001
Kurtosis	-0.4720	-0.4720	-0.4720	-0.4720	-0.4720	-0.4720	-1.3378
Skewness	0.1703	0.1703	0.1703	0.1703	0.1703	0.1703	0.2746
Range	0.0648	0.0648	0.0648	0.0648	0.0648	0.0648	0.0315
Minimum	-0.0056	-0.0056	-0.0056	-0.0056	-0.0056	-0.0056	-0.0026
Maximum	0.0592	0.0592	0.0592	0.0592	0.0592	0.0592	0.0289
Sum	0.4210	0.4210	0.4210	0.4210	0.4210	0.4210	0.2715
Count	20	20	20	20	20	20	20
Confidence	0.0085	0.0085	0.0085	0.0085	0.0085	0.0085	0.0045

Table 59:TSM descriptive statistics during the ESDC using the Hypothetical Portfolio data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	0.0135	0.013	0.0164	0.0134	0.0080	0.0117	0.0135
Standard Error	0.0077	0.0050	0.0049	0.0054	0.0065	0.0073	0.0077
Median	0.0196	0.0072	0.0155	0.0093	0.0039	0.0093	0.0196
Standard Deviation	0.0420	0.0275	0.0267	0.0295	0.0354	0.0402	0.0420
Sample Variance	0.0018	0.0008	0.0007	0.0009	0.0013	0.0016	0.0018
Kurtosis	1.4726	-0.8144	-0.7501	-0.4381	2.2848	2.1298	1.4726
Skewness	-0.5445	-0.2095	-0.2576	-0.3919	-1.1960	-0.4664	-0.5445
Range	0.2178	0.1017	0.1017	0.1131	0.1573	0.2178	0.2178
Minimum	-0.1053	-0.0431	-0.0431	-0.0546	-0.1053	-0.1053	-0.1053
Maximum	0.1125	0.0585	0.0585	0.0585	0.0520	0.1125	0.1125
Sum	0.4059	0.3980	0.4912	0.4033	0.2395	0.3510	0.4059
Count	30	30	30	30	30	30	30
Confidence	0.0157	0.0103	0.0100	0.0110	0.0132	0.0150	0.0157

The average TSM return during the crisis was generally higher than the average TSM return presented in section 5.1.2 of this study, although the Australian average TSM returns significantly underperformed across all TSM periods. This may indicate that the Australian REIT market is more sensitive to market shocks arising from a credit crisis as opposed to a liquidity crisis like the GFC. Marginal outperformance is observed in the US and the global portfolio, but this may not be significant. This outperformance is consistent with the findings of Patari and Vilka (2014) who find that both individual stocks and indices outperform a buy-and-hold strategy during bearish market conditions. The highest average TSM return is found in Brazil over the 2-6 month TSM periods (2.1%), while the lowest average TSM return is found in the UK at the 6 month TSM period (-0.04%).

While the range of TSM returns are lower during the crisis, the rule’s standard deviation is maintained across all markets, with minor deviations from the original dataset and is also lower than the standard deviation of the buy-and-hold strategy. Thus, reinforcing the market timing ability of this strategy during a period of crisis. The MMAC descriptive statistics during the ESDC are shown in tables 60-65 below:

Table 60:MMAC descriptive statistics during the ESDC using US REIT data

	Buy-and-hold	*MMAC rtn*
Mean	0.0126	0.016
Standard Error	0.0096	0.0071
Median	0.0176	0.0147
Standard Deviation	0.0527	0.0387
Sample Variance	0.0028	0.0015
Kurtosis	0.2554	-0.6975
Skewness	-0.1445	-0.0270
Range	0.2504	0.1510
Minimum	-0.1157	-0.0540
Maximum	0.1347	0.0971
Sum	0.3766	0.4780
Count	30	30
Confidence Level(95.0%)	0.0197	0.0145

Table 61:MMAC descriptive statistics during the ESDC using J-REIT data

	Buy-and-hold	*MMAC rtn*
Mean	0.0065	0.015
Standard Error	0.0087	0.0078
Median	-0.0052	0.0010
Standard Deviation	0.0475	0.0426
Sample Variance	0.0023	0.0018
Kurtosis	0.0937	1.5137
Skewness	0.4471	0.5789
Range	0.2095	0.2140
Minimum	-0.0856	-0.0820
Maximum	0.1239	0.1319
Sum	0.1954	0.4589
Count	30	30
Confidence Level(95.0%)	0.0177	0.0159

Table 62:MMAC descriptive statistics during the ESDC using UK REIT data

	Buy-and-hold	*MMAC rtn*
Mean	0.0021	0.013
Standard Error	0.0094	0.0056
Median	0.0036	0.0054
Standard Deviation	0.0512	0.0308
Sample Variance	0.0026	0.0009
Kurtosis	-0.5318	0.4246
Skewness	-0.4042	0.3979
Range	0.1929	0.1392
Minimum	-0.1139	-0.0570
Maximum	0.0790	0.0822
Sum	0.0637	0.3893
Count	30	30
Confidence Level(95.0%)	0.0191	0.0115

Table 63:MMAC descriptive statistics during the ESDC using A-REIT data

	Buy-and-hold	*MMAC rtn*
Mean	0.0022	0.028
Standard Error	0.0057	0.0051
Median	0.0005	0.0469
Standard Deviation	0.0310	0.0281
Sample Variance	0.0010	0.0008
Kurtosis	-0.3226	-0.4302
Skewness	-0.2138	-0.8953
Range	0.1228	0.0981
Minimum	-0.0684	-0.0421
Maximum	0.0545	0.0560
Sum	0.0656	0.8282
Count	30	30
Confidence Level(95.0%)	0.0116	0.0105

Table 64:MMAC descriptive statistics during the ESDC using Brazilian REIT data

	Buy-and-hold	*MMAC rtn*
Mean	0.0210	0.028
Standard Error	0.0041	0.0065
Median	0.0175	0.0223
Standard Deviation	0.0181	0.0292
Sample Variance	0.0003	0.0009
Kurtosis	-0.4720	6.7125
Skewness	0.1703	2.1371
Range	0.0648	0.1332
Minimum	-0.0056	-0.0055
Maximum	0.0592	0.1277
Sum	0.4210	0.5614
Count	20	20
Confidence Level(95.0%)	0.0085	0.0137

Table 65:MMAC descriptive statistics during the ESDC using the Hypothetical Portfolio data

	Buy-and-hold	*MMAC rtn*
Mean	0.0112	0.015
Standard Error	0.0087	0.0065
Median	0.0168	0.0094
Standard Deviation	0.0478	0.0355
Sample Variance	0.0023	0.0013
Kurtosis	0.0409	-0.4879
Skewness	-0.2954	-0.1754
Range	0.2178	0.1447
Minimum	-0.1053	-0.0573
Maximum	0.1125	0.0874
Sum	0.3349	0.4530
Count	30	30
Confidence Level(95.0%)	0.0178	0.0133

With the exception of Japan (1.5%), and Australia (2.8%), the average MMAC returns are consistently lower during the period of the ESDC compared to the average MMAC returns achieved in section 5.1.3. The lowest average MMAC returns during the crisis is found in the UK (1.3%) while the highest average MMAC returns during the crisis is found in Brazil (2.8%). Consistent with the results of the rule during the GFC crisis, the MMAC market timing rule managed to outperform the buy-and-hold strategy in every market selected. Patari and Vilka (2014) also find that both individual stocks and indices outperform a buy-and-hold strategy during bearish market conditions. The outperformance during this crisis may indicate that it is the most resilient strategy of the four. Further, it may indicate that this rule is only mildly sensitive to periods of credit crisis.

The standard deviation of the MMAC rule for every market is also lower than the standard deviation of the data presented in section 5.1.3 as well as the standard deviation of the buy-and-hold strategy. This indicates the market timing ability of the rule even though it limits the upside potential of this rule during the ESDC.

The DM descriptive statistics during the ESDC are shown in tables 66-71 below:

Table 66:DM descriptive statistics during the ESDC using US REIT data

	Buy-and-	*DM rtn*
Mean	0.0126	0.265
Standard Error	0.0096	0.0323
Median	0.0176	0.2421
Standard	0.0527	0.1767
Sample Variance	0.0028	0.0312
Kurtosis	0.2554	0.0801
Skewness	-0.1445	0.7470
Range	0.2504	0.7012
Minimum	-0.1157	0.0126
Maximum	0.1347	0.7139
Sum	0.3766	7.9394
Count	30	30
Confidence	0.0197	0.0660

Table 67:DM descriptive statistics during the ESDC using J-REIT data

	Buy-and-hold	*DM rtn*
Mean	0.0065	0.099
Standard Error	0.0087	0.0207
Median	-0.0052	0.0442
Standard Deviation	0.0475	0.1133
Sample Variance	0.0023	0.0128
Kurtosis	0.0937	-0.8355
Skewness	0.4471	0.7858
Range	0.2095	0.3356
Minimum	-0.0856	-0.0015
Maximum	0.1239	0.3341
Sum	0.1954	2.9573
Count	30	30
Confidence	0.0177	0.0423

Table 68:DM descriptive statistics during the ESDC using UK REIT data

	Buy-and-	*DM rtn*
Mean	0.0021	0.083
Standard Error	0.0094	0.0179
Median	0.0036	0.0421
Standard	0.0512	0.0979
0.00260.00960.00	-0.5318	0.7414
Kurtosis	-0.4042	1.1759
Skewness	0.1929	0.3745
Range	-0.1139	-0.0183
Minimum	0.0790	0.3562
Maximum	0.0637	2.5043
Sum	30	30
Count	0.0191	0.0366
Confidence	0.0021	0.083

Table 69:DM descriptive statistics during the ESDC using A-REIT data

	Buy-and-hold	*DM rtn*
Mean	0.0022	0.048
Standard Error	0.0057	0.0141
Median	0.0005	0.0108
Standard Deviation	0.0310	0.0771
Sample Variance	-0.3226	1.9386
Kurtosis	-0.2138	1.7107
Skewness	0.1228	0.2891
Range	-0.0684	-0.0105
Minimum	0.0545	0.2786
Maximum	0.0656	1.4489
Sum	30	30
Count	0.0116	0.0288
Confidence	0.0022	0.048

Table 70:DM descriptive statistics during the ESDC using Brazilian REIT data

	Buy-and-	*DM rtn*
Mean	0.0304	0.312
Standard Error	0.0063	0.0229
Median	0.0337	0.3180
Standard	0.0189	0.0687
Sample Variance	0.0004	0.0047
Kurtosis	0.2738	-0.9903
Skewness	-0.4646	-0.3851
Range	0.0635	0.2004
Minimum	-0.0043	0.1937
Maximum	0.0592	0.3941
Sum	0.2738	2.8056
Count	9	9
Confidence	0.0145	0.0528

Table 71:DM descriptive statistics during the ESDC using the Hypothetical Portfolio data

	Buy-and-hold	*DM rtn*
Mean	0.0105	0.217
Standard Error	0.0082	0.0269
Median	0.0156	0.2196
Standard Deviation	0.0452	0.1473
Sample Variance	0.0020	0.0217
Kurtosis	-0.0440	-0.1506
Skewness	-0.3798	0.5398
Range	0.1994	0.5799
Minimum	-0.1001	0.0111
Maximum	0.0994	0.5910
Sum	0.3142	6.5095
Count	30	30
Confidence	0.0169	0.0550

The average DM returns are consistently lower during the period of the ESDC compared to average returns achieved over the entire period as seen in section 5.1.4. This reinforces the findings of Antonacci (2014) and Tonnessen (2018) who find that this strategy performs well over longer periods rather than shorter periods. The average DM returns are, however, higher than the average returns of the buy-and-hold strategy during the period of the ESDC. The lowest average return is observed in Australia (4.8%) while the highest average return is observed in Brazil (31.1%). The outperformance is consistent with the findings of Antonacci (2014) who finds that the outperformance under this rule persists throughout severe economic stress.

Unlike during the GFC, the standard deviation during the ESDC is significantly more pronounced for this rule than the standard deviation of the buy-and-hold strategy. While the increased volatility is generally associated with a reduced market timing ability, the risk is justified by the significant excess returns the rule still manages to yield.

During the ESDC, the DM market timing rule proves to be the most resilient since it provides significant excess returns above the buy-and-hold strategy when compared to the other three market timing rules. The US, Brazil, and the global portfolio show the greatest resilience during this crisis since the highest average returns are highest. Further, the market timing ability of the DM rule appears to be greater during the crisis for these markets while the market timing ability of this rule is weaker for Japan, UK, and Australia.

5.3.3 Covid-19

The Covid-19 pandemic is characterised by waves as a form of tracking the number of Covid-19 infections (Salyer et al. 2021). The first wave of COVID-19 peaked at different times for the countries in the sample. Of the countries selected for the sample, SA experienced its peak the latest. To remain consistent with the analysis of the previous crises and in-line with using monthly data, the analysis is conducted until the end of the calendar month following the peak of the first wave of COVID-19 in SA. Milcheva (2021) investigates the effect the Covid-19 pandemic had on the risk-return relationship of US REITs' securities relative to Asian REITs' securities. The author finds that although REITs' securities are resilient during market shocks, the Covid-19 pandemic resulted in many REITs losing significant income. Further, a rise in Covid-19 infections is positively correlated with sharp declines in REITs' returns. The author finds that the performance of REITs during the crisis are more negatively impacted in Asia compared to the US. However, Milcheva (2021) concludes that investors are able to limit their downside risk exposure when implementing trading rules more accurately.

Table 72:MA descriptive statistics during Covid-19 using US REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0008	0.029	0.0216	0.0214	0.0181	0.0152	0.0136
Standard Error	0.0301	0.0114	0.0103	0.0103	0.0115	0.0115	0.0104
Median	0.0191	0.0191	0.0051	0.0043	0.0043	0.0001	0.0001
Standard Deviation	0.0951	0.0361	0.0324	0.0326	0.0363	0.0365	0.0328
Sample Variance	0.0090	0.0013	0.0011	0.0011	0.0013	0.0013	0.0011
Kurtosis	5.3512	0.4686	4.2600	4.2108	2.8551	3.4772	7.3615
Skewness	-2.0366	1.1943	1.9719	1.9613	1.3259	1.5928	2.6894
Range	0.3458	0.1022	0.1022	0.1022	0.1346	0.1346	0.1022
Minimum	-0.2436	0.0000	0.0000	0.0000	-0.0324	-0.0324	0.0000
Maximum	0.1023	0.1023	0.1023	0.1023	0.1023	0.1023	0.1023
Sum	-0.0077	0.2947	0.2155	0.2138	0.1814	0.1518	0.1358
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0680	0.0258	0.0232	0.0233	0.0260	0.0261	0.0235

Table 73:MA descriptive statistics during Covid-19 using J-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0089	0.023	0.0200	0.0093	0.0143	0.0137	0.0058
Standard Error	0.0280	0.0097	0.0107	0.0082	0.0080	0.0081	0.0059
Median	-0.0020	0.0030	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
Standard Deviation	0.0885	0.0307	0.0337	0.0259	0.0253	0.0255	0.0186
Sample Variance	0.0078	0.0009	0.0011	0.0007	0.0006	0.0007	0.0003
Kurtosis	4.9863	-0.9875	-1.1407	1.0138	-0.3745	-0.3653	9.9999
Skewness	-2.0018	0.8657	0.7257	1.5182	1.1473	1.1771	3.1623
Range	0.3118	0.0789	0.0948	0.0748	0.0687	0.0687	0.0589
Minimum	-0.2331	-0.0002	-0.0161	-0.0161	-0.0101	-0.0101	-0.0002
Maximum	0.0787	0.0787	0.0787	0.0587	0.0587	0.0587	0.0587
Sum	-0.0893	0.2322	0.2002	0.0932	0.1435	0.1374	0.0577
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0633	0.0220	0.0241	0.0185	0.0181	0.0183	0.0133

Table 74:MA descriptive statistics during Covid-19 using UK REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0079	0.020	0.0159	0.0153	0.0158	0.0138	0.0036
Standard Error	0.0259	0.0100	0.0098	0.0099	0.0098	0.0099	0.0035
Median	0.0030	0.0030	0.0006	0.0001	0.0001	0.0001	0.0000
Standard Deviation	0.0818	0.0317	0.0309	0.0313	0.0310	0.0313	0.0112
Sample Variance	0.0067	0.0010	0.0010	0.0010	0.0010	0.0010	0.0001
Kurtosis	4.5000	3.4771	6.2156	6.0196	6.1939	6.7472	9.9990
Skewness	-1.7698	1.8636	2.4447	2.3994	2.4406	2.5838	3.1621
Range	0.3072	0.0972	0.0972	0.1025	0.0972	0.0972	0.0356
Minimum	-0.2100	0.0000	0.0000	-0.0053	0.0000	0.0000	-0.0001
Maximum	0.0972	0.0972	0.0972	0.0972	0.0972	0.0972	0.0355
Sum	-0.0787	0.2045	0.1590	0.1527	0.1580	0.1380	0.0356
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0585	0.0227	0.0221	0.0224	0.0222	0.0224	0.0080

Table 75:MA descriptive statistics during Covid-19 using A-REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0091	0.040	0.0216	0.0152	0.0180	0.0174	0.0119
Standard Error	0.0508	0.0170	0.0156	0.0148	0.0142	0.0143	0.0125
Median	0.0014	0.0038	0.0005	0.0008	0.0008	0.0007	0.0004
Standard Deviation	0.1605	0.0536	0.0494	0.0469	0.0449	0.0451	0.0396
Sample Variance	0.0258	0.0029	0.0024	0.0022	0.0020	0.0020	0.0016
Kurtosis	6.7619	-0.9856	0.5526	2.8309	3.2307	3.2594	9.8465
Skewness	-2.3987	0.8902	1.2580	1.8405	1.9858	2.0025	3.1272
Range	0.5640	0.1287	0.1521	0.1521	0.1403	0.1403	0.1334
Minimum	-0.4353	0.0000	-0.0277	-0.0277	-0.0158	-0.0158	-0.0090
Maximum	0.1287	0.1287	0.1244	0.1244	0.1244	0.1244	0.1244
Sum	-0.0905	0.4030	0.2156	0.1515	0.1799	0.1736	0.1192
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.1148	0.0384	0.0353	0.0336	0.0321	0.0323	0.0284

Table 76:MA descriptive statistics during Covid-19 using Brazilian REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0032	0.018	0.0115	0.0097	0.0097	0.0084	0.0107
Standard Error	0.0202	0.0057	0.0065	0.0065	0.0065	0.0067	0.0053
Median	0.0164	0.0164	0.0098	0.0037	0.0037	0.0037	0.0026
Standard Deviation	0.0639	0.0179	0.0205	0.0205	0.0205	0.0213	0.0169
Sample Variance	0.0041	0.0003	0.0004	0.0004	0.0004	0.0005	0.0003
Kurtosis	6.6561	0.4872	2.3861	2.7783	2.7783	2.0827	5.7193
Skewness	-2.4154	1.1215	0.3777	0.6950	0.6950	0.7312	2.3493
Range	0.2270	0.0527	0.0808	0.0808	0.0808	0.0808	0.0527
Minimum	-0.1726	0.0018	-0.0264	-0.0264	-0.0264	-0.0264	0.0018
Maximum	0.0544	0.0544	0.0544	0.0544	0.0544	0.0544	0.0544
Sum	-0.0321	0.1841	0.1155	0.0970	0.0970	0.0843	0.1066
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0457	0.0128	0.0147	0.0146	0.0146	0.0153	0.0121

Table 77:MA descriptive statistics during Covid-19 using SA REIT data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0243	0.053	0.0432	0.0432	0.0432	0.0312	0.0162
Standard Error	0.0611	0.0226	0.0247	0.0247	0.0247	0.0187	0.0130
Median	-0.0209	0.0032	0.0032	0.0032	0.0032	0.0032	0.0032
Standard Deviation	0.1934	0.0713	0.0780	0.0780	0.0780	0.0593	0.0412
Sample Variance	0.0374	0.0051	0.0061	0.0061	0.0061	0.0035	0.0017
Kurtosis	4.3353	-1.0497	-0.9426	-0.9426	-0.9426	1.5956	10.0000
Skewness	-1.7748	0.9822	0.9188	0.9188	0.9188	1.8060	3.1623
Range	0.6754	0.1696	0.2193	0.2193	0.2193	0.1501	0.1303
Minimum	-0.5027	0.0031	-0.0466	-0.0466	-0.0466	0.0031	0.0031
Maximum	0.1727	0.1727	0.1727	0.1727	0.1727	0.1532	0.1335
Sum	-0.2433	0.5252	0.4318	0.4318	0.4318	0.3119	0.1619
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.1383	0.0510	0.0558	0.0558	0.0558	0.0424	0.0295

Table 78:MA descriptive statistics during Covid-19 using the Hypothetical Portfolio data

	Buy-and-hold	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0027	0.028	0.0213	0.0202	0.0148	0.0148	0.0133
Standard Error	0.0301	0.0101	0.0094	0.0096	0.0108	0.0108	0.0099
Median	0.0187	0.0187	0.0120	0.0066	0.0001	0.0001	0.0001
Standard Deviation	0.0951	0.0320	0.0296	0.0302	0.0341	0.0341	0.0311
Sample Variance	0.0091	0.0010	0.0009	0.0009	0.0012	0.0012	0.0010
Kurtosis	6.0302	1.0295	4.6981	4.4726	3.4228	3.4228	6.5975
Skewness	-2.2246	1.2836	2.0301	2.0013	1.5530	1.5530	2.5645
Range	0.3463	0.0958	0.0958	0.0958	0.1261	0.1261	0.0958
Minimum	-0.2504	0.0001	0.0001	0.0001	-0.0302	-0.0302	0.0001
Maximum	0.0959	0.0959	0.0959	0.0959	0.0959	0.0959	0.0959
Sum	-0.0270	0.2816	0.2131	0.2023	0.1478	0.1478	0.1325
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0681	0.0229	0.0212	0.0216	0.0244	0.0244	0.0223

At first glance, the average MA returns during the crisis are not significantly less than the average MA returns presented in section 5.1.1 of this study. However, the maximum returns are significantly reduced under the MA returns in all markets during the Covid-19 pandemic period. Although the upside excess returns are limited, the average returns of the MA market timing rule still outperforms the negative average returns of the buy-and-hold strategy in every market. This is indicative of market timing ability. The lowest average MA return is found in the UK at the 12 month MA period (0.3%), while the highest return is found in SA at the 2 month MA period (5.3%).

The dispersion of returns are fairly constant with marginal differences in the standard deviations for most of the markets selected, with deviation starting decline in the longer MA periods. However, the MA standard deviations are evidently lower than that of the buy-and-hold strategy. This indicates the ability of the rule to limit downside risk exposure consistently as highlighted by Milchev (2021). The reduction in volatility is a further indication of the market timing ability of this rule, since it opts the investor to rotate between the REIT index and a portfolio of T-Bills with accuracy.

Table 79:TSM descriptive statistics during Covid-19 using US REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0008	0.018	0.0126	0.0077	0.0136	0.0034	-0.0084
Standard Error	0.0301	0.0115	0.0122	0.0119	0.0104	0.0033	0.0274
Median	0.0191	0.0043	0.0001	0.0001	0.0001	0.0001	0.0009
Standard Deviation	0.0951	0.0363	0.0386	0.0375	0.0328	0.0104	0.0866
Sample Variance	0.0090	0.0013	0.0015	0.0014	0.0011	0.0001	0.0075
Kurtosis	5.3512	2.8551	2.7584	4.9206	7.3615	9.9999	7.8006
Skewness	-2.0366	1.3259	1.4399	1.9830	2.6894	3.1623	-2.6016
Range	0.3458	0.1346	0.1346	0.1346	0.1022	0.0329	0.3227
Minimum	-0.2436	-0.0324	-0.0324	-0.0324	0.0000	0.0000	-0.2436
Maximum	0.1023	0.1023	0.1023	0.1023	0.1023	0.0329	0.0792
Sum	-0.0077	0.1814	0.1255	0.0770	0.1358	0.0336	-0.0840
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0680	0.0260	0.0276	0.0269	0.0235	0.0074	0.0619

Table 80:TSM descriptive statistics during Covid-19 using J-REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0089	0.009	0.0086	0.0030	0.0092	-0.0234	-0.0131
Standard Error	0.0280	0.0082	0.0104	0.0090	0.0065	0.0233	0.0263
Median	-0.0020	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
Standard Deviation	0.0885	0.0259	0.0328	0.0285	0.0205	0.0737	0.0832
Sample Variance	0.0078	0.0007	0.0011	0.0008	0.0004	0.0054	0.0069
Kurtosis	4.9863	1.0138	0.3238	2.1538	3.6980	10.0000	6.7249
Skewness	-2.0018	1.5182	0.0605	0.2170	2.1149	-3.1623	-2.2966
Range	0.3118	0.0748	0.1104	0.1104	0.0589	0.2330	0.3118
Minimum	-0.2331	-0.0161	-0.0517	-0.0517	-0.0002	-0.2331	-0.2331
Maximum	0.0787	0.0587	0.0587	0.0587	0.0587	-0.0001	0.0787
Sum	-0.0893	0.0932	0.0858	0.0305	0.0920	-0.2339	-0.1307
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0633	0.0185	0.0235	0.0204	0.0146	0.0527	0.0596

Table 81:TSM descriptive statistics during Covid-19 using UK REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0079	0.015	0.0159	0.0153	0.0158	-0.0165	0.0000
Standard Error	0.0259	0.0099	0.0098	0.0099	0.0098	0.0220	0.0000
Median	0.0030	0.0001	0.0006	0.0001	0.0001	0.0000	0.0000
Standard Deviation	0.0818	0.0313	0.0309	0.0313	0.0310	0.0695	0.0001
Sample Variance	0.0067	0.0010	0.0010	0.0010	0.0010	0.0048	0.0000
Kurtosis	4.5000	6.0196	6.2156	6.0196	6.1939	8.9329	-0.4454
Skewness	-1.7698	2.3994	2.4447	2.3994	2.4406	-2.8864	0.4550
Range	0.3072	0.1025	0.0972	0.1025	0.0972	0.2556	0.0002
Minimum	-0.2100	-0.0053	0.0000	-0.0053	0.0000	-0.2100	-0.0001
Maximum	0.0972	0.0972	0.0972	0.0972	0.0972	0.0456	0.0001
Sum	-0.0787	0.1527	0.1590	0.1527	0.1580	-0.1645	0.0001
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0585	0.0224	0.0221	0.0224	0.0222	0.0497	0.0001

Table 82:TSM descriptive statistics during Covid-19 using A-REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0091	0.015	0.0174	0.0100	0.0119	-0.0005	-0.0267
Standard Error	0.0508	0.0148	0.0143	0.0128	0.0125	0.0009	0.0476
Median	0.0014	0.0008	0.0007	0.0004	0.0004	0.0001	0.0000
Standard Deviation	0.1605	0.0469	0.0451	0.0406	0.0396	0.0030	0.1506
Sample Variance	0.0258	0.0022	0.0020	0.0016	0.0016	0.0000	0.0227
Kurtosis	6.7619	2.8309	3.2594	9.4976	9.8465	9.4283	7.7576
Skewness	-2.3987	1.8405	2.0025	3.0464	3.1272	-3.0348	-2.5811
Range	0.5640	0.1521	0.1403	0.1403	0.1334	0.0102	0.5640
Minimum	-0.4353	-0.0277	-0.0158	-0.0158	-0.0090	-0.0090	-0.4353
Maximum	0.1287	0.1244	0.1244	0.1244	0.1244	0.0013	0.1287
Sum	-0.0905	0.1515	0.1736	0.0996	0.1192	-0.0052	-0.2666
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.1148	0.0336	0.0323	0.0290	0.0284	0.0021	0.1078

Table 83:TSM descriptive statistics during Covid-19 using Brazilian REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0032	0.007	0.0032	-0.0131	-0.0094	-0.0076	0.0039
Standard Error	0.0202	0.0067	0.0044	0.0179	0.0187	0.0188	0.0021
Median	0.0164	0.0027	0.0027	0.0020	0.0019	0.0019	0.0030
Standard Deviation	0.0639	0.0213	0.0140	0.0567	0.0592	0.0596	0.0067
Sample Variance	0.0041	0.0005	0.0002	0.0032	0.0035	0.0036	0.0000
Kurtosis	6.6561	2.4629	1.3019	9.3949	8.4060	8.6177	6.9834
Skewness	-2.4154	0.9605	-0.8776	-3.0275	-2.7765	-2.8277	2.4432
Range	0.2270	0.0808	0.0481	0.1942	0.2155	0.2155	0.0241
Minimum	-0.1726	-0.0264	-0.0264	-0.1726	-0.1726	-0.1726	-0.0024
Maximum	0.0544	0.0544	0.0217	0.0217	0.0430	0.0430	0.0217
Sum	-0.0321	0.0711	0.0318	-0.1313	-0.0936	-0.0757	0.0395
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0457	0.0152	0.0100	0.0405	0.0424	0.0426	0.0048

Table 84:TSM descriptive statistics during Covid-19 using SA REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0243	0.033	0.0168	0.0162	0.0162	0.0032	0.0032
Standard Error	0.0611	0.0142	0.0130	0.0130	0.0130	0.0000	0.0000
Median	-0.0209	0.0032	0.0032	0.0032	0.0032	0.0032	0.0032
Standard Deviation	0.1934	0.0448	0.0410	0.0412	0.0412	0.0000	0.0000
Sample Variance	0.0374	0.0020	0.0017	0.0017	0.0017	0.0000	0.0000
Kurtosis	4.3353	1.5625	9.9367	10.0000	10.0000	-1.6950	-1.6950
Skewness	-1.7748	1.4335	3.1491	3.1623	3.1623	0.3196	0.3196
Range	0.6754	0.1303	0.1303	0.1303	0.1303	0.0001	0.0001
Minimum	-0.5027	0.0031	0.0031	0.0031	0.0031	0.0031	0.0031
Maximum	0.1727	0.1335	0.1335	0.1335	0.1335	0.0032	0.0032
Sum	-0.2433	0.3336	0.1681	0.1619	0.1619	0.0317	0.0317
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.1383	0.0320	0.0294	0.0295	0.0295	0.0000	0.0000

Table 85:TSM descriptive statistics during Covid-19 using SA REIT data

	Buy-and-	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Mean	-0.0027	0.017	0.0087	0.0074	0.0133	-0.0214	-0.0114
Standard Error	0.0301	0.0107	0.0113	0.0114	0.0099	0.0257	0.0275
Median	0.0187	0.0066	0.0001	0.0001	0.0001	0.0001	0.0001
Standard Deviation	0.0951	0.0338	0.0359	0.0359	0.0311	0.0813	0.0869
Sample Variance	0.0091	0.0011	0.0013	0.0013	0.0010	0.0066	0.0075
Kurtosis	6.0302	3.0294	3.8874	4.2371	6.5975	9.4977	8.3636
Skewness	-2.2246	1.3394	1.7206	1.8456	2.5645	-3.0407	-2.7560
Range	0.3463	0.1261	0.1261	0.1261	0.0958	0.2863	0.3190
Minimum	-0.2504	-0.0302	-0.0302	-0.0302	0.0001	-0.2504	-0.2504
Maximum	0.0959	0.0959	0.0959	0.0959	0.0959	0.0359	0.0686
Sum	-0.0270	0.1721	0.0875	0.0744	0.1325	-0.2139	-0.1137
Count	10	10	10	10	10	10	10
Confidence Level(95.0%)	0.0681	0.0242	0.0257	0.0257	0.0223	0.0581	0.0621

The average TSM returns provide random under- and overperformance compared to the average TSM returns discussed in section 5.1.2 of this study. However, they outperform the average TSM return of the buy-and-hold strategy for every period during this crisis. The lowest average TSM is found in Brazil at the 5 month TSM period (-0.94%) while the highest average TSM return is found in SA at the 2 month TSM period (3.3%). Although some average TSM returns are positive, while others are negative, the outperformance against the buy-and-hold strategy is indicative of market timing ability during this crisis.

During the crisis, the standard deviation of the respective buy-and-hold strategies range from 6.4% (Brazil) to 19.3% (SA). The standard deviation of the TSM results range from 0.3% to 15% both in Australia. The lower volatility range of the TSM compared to the higher volatility of the buy-and-hold strategy indicates that this market timing rule retains its market timing ability throughout this crisis.

Table 86:MMAC descriptive statistics during Covid-19 using US REIT data

	Buy-and-hold	*MMAC*
Mean	-0.0008	0.016
Standard Error	0.0301	0.0107
Median	0.0191	0.0010
Standard Deviation	0.0951	0.0339
Sample Variance	0.0090	0.0012
Kurtosis	5.3512	7.5654
Skewness	-2.0366	2.7152
Range	0.3458	0.1071
Minimum	-0.2436	0.0005
Maximum	0.1023	0.1077
Sum	-0.0077	0.1556
Count	10	10
Confidence	0.0680	0.0243

Table 87:MMAC descriptive statistics during Covid-19 using J-REIT data

	Buy-and-hold	*MMAC*
Mean	-0.0089	0.004
Standard Error	0.0280	0.0063
Median	-0.0020	-0.0011
Standard Deviation	0.0885	0.0200
Sample Variance	0.0078	0.0004
Kurtosis	4.9863	9.4917
Skewness	-2.0018	3.0398
Range	0.3118	0.0704
Minimum	-0.2331	-0.0100
Maximum	0.0787	0.0604
Sum	-0.0893	0.0406
Count	10	10
Confidence	0.0633	0.0143

Table 88:MMAC descriptive statistics during Covid-19 using UK REIT data

	Buy-and-hold	*MMAC*
Mean	-0.0079	0.014
Standard Error	0.0259	0.0104
Median	0.0030	0.0005
Standard Deviation	0.0818	0.0329
Sample Variance	0.0067	0.0011
Kurtosis	4.5000	6.9244
Skewness	-1.7698	2.6166
Range	0.3072	0.1027
Minimum	-0.2100	-0.0006
Maximum	0.0972	0.1021
Sum	-0.0787	0.1411
Count	10	10
Confidence	0.0585	0.0235

Table 89:MMAC descriptive statistics during Covid-19 using A-REIT data

	Buy-and-hold	*MMAC*
Mean	-0.0091	0.019
Standard Error	0.0508	0.0150
Median	0.0014	0.0012
Standard Deviation	0.1605	0.0473
Sample Variance	0.0258	0.0022
Kurtosis	6.7619	3.4151
Skewness	-2.3987	2.0162
Range	0.5640	0.1482
Minimum	-0.4353	-0.0157
Maximum	0.1287	0.1325
Sum	-0.0905	0.1934
Count	10	10
Confidence	0.1148	0.0338

Table 90:MMAC descriptive statistics during Covid-19 using Brazilian REIT data

	Buy-and-hold	*MMAC*
Mean	-0.0032	0.022
Standard Error	0.0202	0.0055
Median	0.0164	0.0215
Standard Deviation	0.0639	0.0175
Sample Variance	0.0041	0.0003
Kurtosis	6.6561	1.4750
Skewness	-2.4154	0.1611
Range	0.2270	0.0660
Minimum	-0.1726	-0.0101
Maximum	0.0544	0.0559
Sum	-0.0321	0.2156
Count	10	10
Confidence	0.0457	0.0125

Table 91:MMAC descriptive statistics during Covid-19 using SA REIT data

	Buy-and-hold	*MMAC*
Mean	-0.0243	0.048
Standard Error	0.0611	0.0105
Median	-0.0209	0.0380
Standard Deviation	0.1934	0.0332
Sample Variance	0.0374	0.0011
Kurtosis	4.3353	9.9970
Skewness	-1.7748	3.1616
Range	0.6754	0.1052
Minimum	-0.5027	0.0376
Maximum	0.1727	0.1428
Sum	-0.2433	0.4840
Count	10	10
Confidence	0.1383	0.0237

Table 92:MMAC descriptive statistics during Covid-19 using the Hypothetical Portfolio data

	Buy-and-hold	*MMAC*
Mean	-0.0027	0.014
Standard Error	0.0301	0.0102
Median	0.0187	0.0008
Standard Deviation	0.0951	0.0323
Sample Variance	0.0091	0.0010
Kurtosis	6.0302	6.8348
Skewness	-2.2246	2.6029
Range	0.3463	0.1000
Minimum	-0.2504	0.0007
Maximum	0.0959	0.1006
Sum	-0.0270	0.1441
Count	10	10
Confidence	0.0681	0.0231

The average MMAC returns achieved are consistently higher than the average returns of the buy-and-hold strategy during this crisis. The lowest average MMAC return during the crisis is found in Japan (0.4%) while the highest average MMAC return during the crisis is found in SA (4.8%). The conclusion of Patari and Vilka (2014) also applies during this crisis, since markets such as the UK and SA, displayed even greater excess returns than they would under normal market conditions. This type of outperformance is mildly observed by the average MMAC returns during the former two crises. This is indicative of the strong market timing ability exhibited by this rule.

The standard deviation of the MMAC rule for every market are significantly lower than the standard deviation of the buy-and-hold strategy. This indicates that the rule provides an overall reduction in risk and consistently rotates between the REIT index and a portfolio of T-Bills consistently. Therefore, providing merit the use of the MMAC as a market timing rule.

Table 93:DM descriptive statistics during Covid-19 using US REIT data

	Buy-and-hold	*DM*
Mean	-0.0008	0.004
Standard Error	0.0301	0.0028
Median	0.0191	0.0035
Standard Deviation	0.0951	0.0088
Sample Variance	0.0090	0.0001
Kurtosis	5.3512	-1.1089
Skewness	-2.0366	0.1742
Range	0.3458	0.0260
Minimum	-0.2436	-0.0089
Maximum	0.1023	0.0171
Sum	-0.0077	0.0380
Count	10	10
Confidence Level(95.0%)	0.0680	0.0063

Table 94:DM descriptive statistics during Covid-19 using J-REIT data

	Buy-and-	*DM*
Mean	-0.0089	-0.002
Standard Error	0.0280	0.0018
Median	-0.0020	-0.0004
Standard Deviation	0.0885	0.0055
Sample Variance	0.0078	0.0000
Kurtosis	4.9863	4.2437
Skewness	-2.0018	-1.8656
Range	0.3118	0.0186
Minimum	-0.2331	-0.0156
Maximum	0.0787	0.0030
Sum	-0.0893	-0.0186
Count	10	10
Confidence	0.0633	0.0040

Table 95:DM descriptive statistics during Covid-19 using UK REIT data

	Buy-and-hold	*DM*
Mean	-0.0079	0.006
Standard Error	0.0259	0.0109
Median	0.0030	0.0127
Standard Deviation	0.0818	0.0344
Sample Variance	0.0067	0.0012
Kurtosis	4.5000	4.3428
Skewness	-1.7698	-1.3449
Range	0.3072	0.1373
Minimum	-0.2100	-0.0763
Maximum	0.0972	0.0610
Sum	-0.0787	0.0615
Count	10	10
Confidence Level(95.0%)	0.0585	0.0246

Table 96:DM descriptive statistics during Covid-19 using A-REIT data

	Buy-and-	*DM*
Mean	-0.0091	0.001
Standard Error	0.0508	0.0015
Median	0.0014	0.0008
Standard Deviation	0.1605	0.0046
Sample Variance	0.0258	0.0000
Kurtosis	6.7619	1.7310
Skewness	-2.3987	1.1598
Range	0.5640	0.0157
Minimum	-0.4353	-0.0041
Maximum	0.1287	0.0115
Sum	-0.0905	0.0131
Count	10	10
Confidence	0.1148	0.0033

Table 97:DM descriptive statistics during Covid-19 using Brazilian REIT data

	Buy-and-hold	*DM*
Mean	-0.0032	0.023
Standard Error	0.0202	0.0148
Median	0.0164	0.0350
Standard Deviation	0.0639	0.0467
Sample Variance	0.0041	0.0022
Kurtosis	6.6561	7.1764
Skewness	-2.4154	-2.5036
Range	0.2270	0.1712
Minimum	-0.1726	-0.1026
Maximum	0.0544	0.0686
Sum	-0.0321	0.2262
Count	10	10
Confidence Level(95.0%)	0.0457	0.0334

Table 98:DM descriptive statistics during Covid-19 using SA REIT data

	Buy-and-	*DM*
Mean	-0.0243	0.005
Standard Error	0.0611	0.0029
Median	-0.0209	0.0057
Standard Deviation	0.1934	0.0091
Sample Variance	0.0374	0.0001
Kurtosis	4.3353	-1.3206
Skewness	-1.7748	0.0594
Range	0.6754	0.0269
Minimum	-0.5027	-0.0075
Maximum	0.1727	0.0194
Sum	-0.2433	0.0496
Count	10	10
Confidence	0.1383	0.0065

Table 99:DM descriptive statistics during Covid-19 using the Hypothetical Portfolio data

	Buy-and-hold	*DM*
Mean	-0.0030	0.003
Standard Error	0.0296	0.0028
Median	0.0183	0.0035
Standard Deviation	0.0937	0.0090
Sample Variance	0.0088	0.0001
Kurtosis	6.2172	-0.5051
Skewness	-2.2819	-0.1361
Range	0.3400	0.0288
Minimum	-0.2482	-0.0118
Maximum	0.0918	0.0170
Sum	-0.0296	0.0299
Count	10	10
Confidence Level(95.0%)	0.0670	0.0064

The average DM returns are consistently higher than the average buy-and-hold strategy over the period of the first wave of Covid-19. The lowest average return under the DM market timing rule is found in Japan (-0.1%) while the highest average return is found in the UK (0.6%). While the DM rule does outperform the buy-and-hold strategy, the returns do not appear to be meaningful. The insignificant returns are justified by Antonacci (2014) who finds that the DM market timing rule provides the greatest excess returns over long periods of observation and poor excess returns over short periods.

The standard deviation of the buy-and-hold strategy ranges from 6.4% (Brazil) to 19.3% (SA) whereas the standard deviation of the DM market timing rule ranges from 0.4% (Australia) to 3.4% (UK). The sharp decline in the volatility is directly correlated to an increase in the market timing ability of this rule. Therefore, although not significant, the DM market timing rule does hold market timing ability during the Covid-19 pandemic.

5.4 Summary of the effectiveness of the market timing rules during periods of crises

Evidently, all four market timing rules were able to retain their predictive ability during all three crises, with the MMAC and DM market timing rules exhibiting the greatest resilience. The results of the market timing rules during the all three crises indicated that the US REIT market is the most resilient market since it yielded the highest average return. This is because the US REIT market is the most mature market compared to the other markets selected in this study. The results also indicated that the predictive ability of the rules increased as their standard deviations decreased. The results of the MA and TSM market timing rules appear to be closely correlated while the returns for the rules were greatest with the implementation of the MMAC and DM market timing rules. The DM market timing rule yielded the highest returns compared to the three former strategies, in all three crises. The outperformance of the DM market timing rule is largely attributable to it recovering less losses during periods of market recovery

5.5 Chapter summary

This chapter presented and discussed the four market timing rules applied in this study. The results indicated that all four market timing rules were able to outperform the buy-and-hold strategy. This predictive ability was exhibited by a general decrease in the standard deviation of the strategies. Many of the findings were consistent with the findings of the studies in chapter 2 of this study. This adds to the reliability of the market timing rules. It was also found that more mature markets experienced less outliers as opposed to less mature markets where more outliers were found. This is largely attributable to REITs being more thinly traded in less mature markets. As the concluding chapter, chapter 6 will provide an overall summary of this study through reviewing the research objectives and questions presented in chapter 1 of this study. Chapter 6 will also discuss the implications of this study's findings and provide recommendations for future research in the area of market timing REITs.

Chapter 6

6.1 Summary

This study employed monthly data for the period January 2001 to December 2021. This period is selected since REITs have become more actively traded in some markets in more recent years. This period also provides insight into the effectiveness of the selected market timing rules during three prominent crises, namely: (i) the GFC; (ii) ESDC; and the (iii) Covid-19 pandemic. The analysis investigated the market timing ability within six of the largest REITs markets globally. A seventh hypothetical portfolio was also constructed to provide insight into the effective of market timing for a global REIT investor.

In terms of the first research objective, the results indicated that all four market timing rules consistently outperform the buy-and-hold strategy. The overall risk inherent in applying these rules was less than the overall risk of the buy-and-hold strategy, thus, indicating predictive ability. However, some rules provided more predictive ability than others. It was observed that the MA and TSM market timing rules perform very similarly, with the TSM rule capturing high positive excess returns during market downturns. This similarity is attributable to the fact that the average returns under both strategies start to converge to the returns of the buy-and-hold strategy in periods greater than 6 months. The MMAC market timing rule outperformed both the MA and TSM, especially during bearish market cycles. This increased outperformance was directly attributable to a decrease in the correlation of returns to the returns of the buy-and-hold strategy. The DM market timing rule provides a contrarian approach to market timing compared to the former three rules, which allows it yield the greatest range of risk-adjusted returns. Unlike the previous rules, the DM rule has greater predictive ability over longer periods as opposed to shorter periods. This rule also provides optimal returns during bullish market conditions rather than bearish market conditions.

The secondary objective of this study was to test the ability of the market timing rules to retain their predictive ability during three market crises. The results indicated that all four market timing rules maintained their predictive ability, with the MMAC and DM market timing rules consistently exhibiting the greatest resilience. The MA and TSM market timing rules yielded weaker returns indicating potential sensitivity to liquidity and credit market shocks, respectively. Overall, the

DM market timing rule yielded the highest risk-adjusted returns which are mainly attributable to the rule's ability to recovering less losses during periods of market recovery.

6.2 Implications of this study

The consistent outperformance of the rules provides an indication that market inefficiencies exist for investors to exploit. The profitability of the rules us thus largely dependent on investors correctly identifying the market cycle and aligning that to the most appropriate market timing rule for the identified market cycle. A misalignment in this regard may result in the market timing rules underperforming their buy-and-hold counterparts, thus providing poor evidence of predictive ability. This may result in a violation of the EMH and thus an inaccurate recommendation for passive investing.

Smaller sample size affects the successful implementation of market timing rules, such as the DM market timing rule, which tend to perform well over longer periods of observation. Literature reviewed in chapter 2 of this study generally increased their sample size through the use of daily observations instead of monthly observations. The analysis across multiple markets in monthly intervals, as with this study, may also be a viable option but may limit the insight for users of market timing rules who are typically traders.

Since REIT markets such as Australia, Brazil, and SA are still growing, the REIT returns will be more volatile because of thin trading. In order to correctly attribute excess returns to the predictive ability of the market timing rules, REIT policy makers could align the valuation models of REITs in less mature markets to that of more mature markets such as the US. This ensures greater resilience and consistency in excess returns purely attributable to the market timing rules. Chapter 5 highlighted that transaction costs may be a potential factor in reducing the excess returns achieved by the market timing rules. The introduction of automated trading signals may be of use to maximise the returns to investors trading at a large scale.

6.3 Recommendations for further research

This study focused on determining whether market timing rules may be applied to REITs, and whether these rules retain their effectiveness over crisis periods. The studies of De Chassart and Dumont (2002) and Anghel (2013) are only some that indicate that there are fundamental factors, such market conditions, that affect the effectiveness of the market timing rules. Although not within the scope of this study, there is scope for future research to investigate the fundamental factors that affect these rules by introducing factor models and corresponding regressions to test the strength of the relevant factors.

The current research was limited to observing monthly returns. Although this was mitigated by providing cross country comparisons, researching the predictive ability of the market timing rules using daily returns may provide greater accuracy into the optimal periods to be used under all four market timing rules. REITs contain subsectors that have different factors that affect their performance, especially during crisis periods (Milcheva, 2020). In many markets, investors are able to invest in specific REIT subsectors. It may thus be insightful to expand the sample by assessing and comparing the effectiveness of market timing rules across the different sub-sectors of REITs.

6.4 Conclusion

The fluctuations in the prices of listed securities have continuously provided investors with the opportunity to realise short-term profit from this market volatility. To this end, the scope for implementing market timing rules always exists. The primary objective of this study was to investigate the effectiveness of market timing rules in the REITs sector, from the perspective of the investor and to determine whether the effectiveness of these rules, if any, persists through market crises. The analysis revealed that all four market timing rules outperformed their buy-and-hold counterparts consistently, thus providing market timing ability. It was also observed that the predictive ability of the market timing rules persisted throughout the various market crises. In general, the MA and TSM market timing rules exhibited very similar performance while the MMAC and DM market timing rules exhibited the highest returns. Of the four market timing rules, the DM market timing rule exhibited the highest return with the lowest overall risk, indicating that it has the highest predictive ability of the four rules.

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Appendix A

The following t-bill proxies were used in this analysis:

7.1 T-bill proxies

Country	**Proxy**
US	US 3 Month Treasury
Japan	Japan Generic Government 3 Month Yield
UK	United Kingdom 3 Month Bill Yield
Australia	Australia Treasury Bill Rate: Government Securities
Brazil	IMF Brazil Treasury Bill Rate
South Africa	SARB Treasury bills - 91 day (tender rates)
Hypothetical Portfolio	Weighted Average of above 6 indices

The following bond proxies were used in this analysis:

7.2 Bond proxies

Country	**Proxy**
US	FTSE US Broad Investment-Grade Bond Index
Japan	S&P Japan Bond Index
UK	S&P UK Investment Grade Corporate Bond Index
Australia	FTSE Australian Broad Investment-Grade Bond Index
Brazil	IRF-M, National Treasury Letters (LTNs) and National Treasury Notes – Series F (NTN-Fs), representing fixed-rate bonds.
South Africa	FTSE/JSE All Bond Index
Hypothetical Portfolio	Weighted Average of above 6 indices

The following indices were used in this analysis:

7.3 Alternative indices

Country	**Proxy**
US	S&P 500 Index
Japan	Tokyo Stock Price Index
UK	FTSE 100 Index
Australia	S&P/ASX 200 Index
Brazil	Ibovespa Brasil Sao Paulo Stock Exchange Index
South Africa	FTSE/JSE Africa All Share Index
Hypothetical Portfolio	Weighted Average of above 6 indices

Appendix B:Correlations

7.4 MA correlations using US REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.7398	1					
3-month	0.7005	0.9614	1				
4-month	0.6677	0.8868	0.9170	1			
5-month	0.6618	0.8787	0.9029	0.9789	1		
6-month	0.6529	0.8657	0.8844	0.9567	0.9766	1	
12-month	0.6116	0.6695	0.6699	0.7348	0.7441	0.7544	1

7.5 MA correlations using J-REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.7764	1					
3-month	0.7564	0.9885	1				
4-month	0.7115	0.9370	0.9463	1			
5-month	0.7144	0.9380	0.9458	0.9924	1		
6-month	0.7440	0.8688	0.8724	0.9116	0.9183	1	
12-month	0.7810	0.8187	0.8111	0.8200	0.8222	0.8899	1

7.6 MA correlations using UK REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.7420	1					
3-month	0.7050	0.9697	1				
4-month	0.6748	0.9370	0.9553	1			
5-month	0.6651	0.9104	0.9239	0.9633	1		
6-month	0.6587	0.9050	0.9189	0.9467	0.9816	1	
12-month	0.5803	0.7112	0.7137	0.7361	0.7732	0.7915	1

7.7 MA correlations using A-REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.6541	1					
3-month	0.6088	0.9249	1				
4-month	0.5835	0.8532	0.9154	1			
5-month	0.5658	0.8177	0.8719	0.9494	1		
6-month	0.5609	0.8075	0.8597	0.9251	0.9747	1	
12-month	0.5438	0.7450	0.7813	0.8296	0.8718	0.8938	1

7.8 MA correlations using Brazilian REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.7395	1					
3-month	0.7030	0.9336	1				
4-month	0.6911	0.9079	0.9649	1			
5-month	0.6895	0.9010	0.9536	0.9863	1		
6-month	0.6942	0.8921	0.9350	0.9592	0.9718	1	
12-month	0.7026	0.8753	0.8966	0.9180	0.9300	0.9545	1

7.9 MA correlations using SA REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.6154	1					
3-month	0.5926	0.9742	1				
4-month	0.5789	0.9564	0.9765	1			
5-month	0.5628	0.9358	0.9519	0.9751	1		
6-month	0.4903	0.7752	0.7733	0.8047	0.8299	1	
12-month	0.4282	0.5942	0.5897	0.6202	0.6375	0.7662	1

7.10 MA correlations using the Hypothetical Portfolio REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.7320	1					
3-month	0.6816	0.9366	1				
4-month	0.6747	0.9145	0.9665	1			
5-month	0.6687	0.8992	0.9300	0.9561	1		
6-month	0.6462	0.8602	0.8890	0.9165	0.9611	1	
12-month	0.6164	0.7296	0.7507	0.7791	0.8123	0.7760	1

TSM correlations

7.11 TSM correlations using US REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.6067	1					
3-month	0.5847	0.7209	1				
4-month	0.5898	0.6973	0.9209	1			
5-month	0.6123	0.6317	0.7932	0.8609	1		
6-month	0.6137	0.5405	0.6954	0.7611	0.9047	1	
12-month	0.6841	0.4700	0.6105	0.6246	0.7377	0.8086	1

7.12 TSM correlations using J-REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.7218	1					
3-month	0.7142	0.8635	1				
4-month	0.7232	0.7709	0.8984	1			
5-month	0.7348	0.7754	0.8096	0.9114	1		
6-month	0.7872	0.7049	0.7262	0.8127	0.8946	1	
12-month	0.8381	0.7230	0.7187	0.7175	0.7612	0.8513	1

7.13 TSM correlations using UK REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.6774	1					
3-month	0.7438	0.8567	1				
4-month	0.7128	0.8805	0.9553	1			
5-month	0.7033	0.9039	0.9239	0.9633	1		
6-month	0.6443	0.5788	0.5289	0.5278	0.5439	1	
12-month	0.6203	0.5070	0.5357	0.5106	0.5201	0.6788	1

7.14 TSM correlations using A-REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.5308	1					
3-month	0.5294	0.8113	1				
4-month	0.5304	0.7100	0.8756	1			
5-month	0.5110	0.6951	0.7688	0.8729	1		
6-month	0.4973	0.6227	0.6244	0.7303	0.8588	1	
12-month	0.7666	0.3756	0.4082	0.4479	0.4832	0.5441	1

7.15 TSM correlations using Brazilian REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.6952	1					
3-month	0.6724	0.7966	1				
4-month	0.8080	0.6165	0.7530	1			
5-month	0.8320	0.6115	0.7136	0.9545	1		
6-month	0.8893	0.5780	0.6679	0.8915	0.9328	1	
12-month	0.3265	0.2576	0.3087	0.2983	0.3105	0.3453	1

7.16 TSM correlations using SA REIT data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.4684	1					
3-month	0.2870	0.7205	1				
4-month	0.3032	0.6353	0.8867	1			
5-month	0.2977	0.6631	0.8438	0.9408	1		
6-month	0.3790	0.4076	0.2726	0.3323	0.2820	1	
12-month	0.4072	0.3977	0.2390	0.2884	0.2688	0.9177	1

7.17 TSM correlations using the Hypothetical Portfolio data

	Lognormal rtn	*2-month*	*3-month*	*4-month*	*5-month*	*6-month*	*12-month*
Lognormal rtn	1						
2-month	0.6217	1					
3-month	0.5929	0.7939	1				
4-month	0.5910	0.7785	0.9200	1			
5-month	0.6202	0.6974	0.8204	0.8945	1		
6-month	0.6824	0.5528	0.6512	0.7165	0.8147	1	
12-month	0.7056	0.5277	0.6011	0.6448	0.7275	0.8968	1